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Three Essays on “Production and Technical Efficiency”

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THREE ESSAYS ON “PRODUCTION AND TECHNICAL EFFICIENCY”

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ABSTRACT

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This dissertation examines production and or technical efficiencies in agricultural and energy systems. First, I focus on the agriculture system, looking at corn production, which is not only grown for food but also an important renewable energy source. Second, I examine efficiency and inter-fuel substitution in the production of electricity. Lastly, I examine the role of drilled but uncompleted wells in natural gas production.

The first essay examines production capabilities of smallholder corn farmers following Zimbabwe's fast track land reform program of 2000. This paper accounts for various production frontiers to provide more reliable efficiency estimates than can be obtained using traditional parametric methods. I also use a semi-parametric model, which allows for flexible production function and assumes that exogenous variables directly affect output. I find that observed production shortfalls can be significantly mitigated by implementing appropriate government programs that focus on gender, age, extension services and inclusion of other crops.

The second essay examines efficiency and state level fuel substitution in the US electricity generation sector. Previous studies used aggregate data to evaluate fuel substitutability implicitly assuming uniformity of policy implications across regions. This can produce biased estimates of policy effects at the (sub)regional levels, which can potentially lead to suboptimal policy recommendations. Understanding spatial variations in inter-fuel substitution patterns across states is important for effective policy design as the response of power producers to policies differs depending on technological endowments, fuel availability, environmental

regulation, and institutional contexts. I apply the recent fixed effects stochastic frontier estimation to understand the implications of changes in inter-fuel substitution for technical efficiency. Findings demonstrate that regional fossil-fuel utilization in electricity generation depends on fuel substitution and the capability of power producers to respond to fuel price changes. These findings illustrate the need for careful regional analysis and design of electricity policies, especially given anticipated retirements of power generation units. I also find that increase in substitution capabilities has positive effects on efficiency and reduction of CO_2 emissions.

The third essay examines the role of drilled but uncompleted wells (DUCs) in the US natural gas production. Prior studies have used drilling rig activity (measured by rig count) as a major predictor of oil and gas production. However, in the last decade, correlation between production and drilling rig activity weakened, raising doubts about the suitability of rig count as the major driver. This study considers variations in producing, newly completed and drilled but uncompleted wells to understand the current production of natural gas. The results show a significant relationship between well completion and natural gas output, but the strength of the relationship differs across US regions. The weakening of the relationship between drilling rig activity and natural gas production is due to the increase in the number of drilled but uncompleted wells, which in turn depends on natural gas prices and pipeline capacity. Among other variables examined, oil and gas prices, pipeline capacity and well length significantly determine the length of time taken to complete drilled wells.

DEDICATION

I would like to dedicate my dissertation to my family: my lovely and supporting wife, Itai Lorraine; my beautiful princesses Kelsy Ruvarashe and Kacey Ruvimbo and handsome prince Douglas Kayden Jr.

I would also like to dedicate my research to my caring parents: my mother Mrs. Bessie Mugabe and my father, the late Mr. Caiphas Mugabe and my humble inlaws Mrs Flora Jaure and the late, Mr. Casper Jaure.

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NOMENCLATURE

Bcf	Billion Cubic Feet
BTU	British Thermal Units
CO_2	Carbon Dioxide
DFA	Deterministic Frontier Analysis
DI	DrillingInfo
DUC	Drilled but Un-Completed Well
EIA	Energy Information Administration
EPA	Energy Policy Act
FAO	Food and Agriculture Organization of the United Nations
FTLRP	Fast Track Land Reform Programme
GAM	Generalized Additive Model
GAMLSS	Generalized Additive Models for Location, Scale and Shape
GW	Gigawatt
LRT	Likelihood Ratio Test
Mcf	Thousand Cubic Feet
MMSLE	Marginalized Maximum Simulated Likelihood Estimation
NYMEX	New York Mercantile Exchange
OLS	Ordinary Least Squares
RPS	Renewable Portfolio Standards
SEDS	State Energy Data System
SEMSFA	Semiparametric Estimation of Stochastic Frontier Models
SF	Stochastic Frontier
TFE-MLE	True Fixed Effects Regression Through Maximum Likelihood Estimation
UOG	Unconventional Oil and Gas
US	United States
USDA	United States Department of Agriculture
US-EPA	United States-Environmental Protection Agency
VAR	Vector Auto Regression
VEC	Vector Error Correction
WMLE	Within-Maximum Likelihood Estimation

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To the Almighty God, who make all things possible, may your name be exalted.

CHAPTER 1. How efficient is maize production among smallholder farmers in Zimbabwe? A comparison of semiparametric and parametric frontier efficiency analyses.

Abstract

The controversial Fast Track Land Reform Programme in Zimbabwe that redistributes commercially owned farmland to smallholder households has caused concerns about the efficiency of agricultural production in the country. In this paper, I estimate the efficiency of resource use among smallholder farmers in Zimbabwe when producing maize, the staple crop in the country. Using both a semiparametric model and a fully parametric stochastic frontier model, I find significant production shortfalls for smallholder maize production. While labor, capital, and land all significantly affect the total output, the estimated mean efficiency score for farms with less than 10 hectares of land(A1) appears to be under 0.75, and for the entire sample (A1 and A2) it ranges between 0.595 and 0.772. There clearly exists a great potential for maize farmers to improve the technical efficiency and increase the total output. Gender and age of the household head, access to extension services, and activities for other crops significantly affect the technical efficiency of smallholder maize production in Zimbabwe. I also find that all farms operate under increasing returns to scale and that the technical efficiency score tends to increase with the level of output.

Keywords: Stochastic frontier; maize production; Zimbabwe; Fast Track Land Reform Programme; contextual variables; semi-parametric model

JEL CLASSIFICATION: Q12; C14; N57

1.1 Introduction

Agricultural production is one of the primary economic sectors in Zimbabwe and represents the livelihood of most of the poor in the country. However, one of the key inputs to its agricultural production, land, had been largely occupied by large-scale commercial farms prior to Zimbabwe's independence in 1980[1]. Since the 1980s, the Zimbabwean government has been actively pursuing land reform and resettlement policies that aim to reverse the racially skewed agricultural land-ownership pattern. In 2000, the government started the Fast Track Land Reform Programme (FTLRP), targeting to acquire at least five million hectares of landpreviously owned by large commercial farmers for redistribution. Under the FTLRP, A1 and A2 farm models were created, replacing large commercial farmers with rural communal farmers[2]. A1 model farms are small plots usually with less than 10 hectares of arable land allocated to farmers, while A2 model includes farms with plots typically above 10 hectares grouped into small, medium and large farms (Cliffe et al. 2013). Currently, more than 35 percent of arable land in Zimbabwe has been reallocated to smallholder farmers among 161,500 families since the implementation of the FTLRP, resulting in 145,000 A1 and 16,500 A2 farmers (Pallotti and Tornimbeni 2015; Scoones et al. 2011).

Traditionally, smallholder farmers are characterized with little or no investment in agricultural production due to limited access to agricultural input and output markets, insecurity in land tenure systems, opportunities in off-farm employment and imperfection in local agricultural and credit markets. As a result, some market analysts and researchers have argued that the efficiency of agricultural production in Zimbabwe has deteriorated after the FTLRP, which essentially replaced efficiently-run commercial farms with smallholder farms lacking the ability to optimally utilize the

[1]Shaw (2003) reports that 45 percent of agricultural land in Zimbabwe was occupied by less than 1 percent of the population in 1980.

[2]Currently, Zimbabwe's land ownership falls into four categories: communal, old resettlement, A1, and small-scale commercial and A2. USDA (2018) reports that in 2018, A1 and A2 farmers produced about 26% and 31% of the country's maize, respectively.

available resources (Cliffe et al. 2013; Davies 2005; Moyo 2004; Zikhali 2010). Indeed, Zikhali (2010) evaluated the impact of FTLRP on agricultural production in Zimbabwe and found that beneficiaries of the program were reluctant to invest in soil conservation due to a lack of tenure security, adversely affecting crop production in the country.[3]

A handful of empirical studies have evaluated the technical efficiency of agricultural production in Zimbabwe after the implementation of the FTLRP. Bangwayo-Skeete, Bezabih, and Zikhali (2010) estimated that beneficiaries of the FTLRP in Mashonaland Central province had an average of only 37.3% production efficiency (i.e., the total output relative to the potential output possible based on available resources), though this number is considerably higher than communal farmers that applied for the program but were rejected. Obi and Chisango (2011) analyzed the performance of resettled smallholder farmers under limited mechanization and the FTLRP, finding a high degree of inefficiencies in resource use in the smallholder system. Richardson (2004) reported that agricultural production in Zimbabwe encountered a 30% drop in 2004 after the FTLRP was implemented. Chitiga and Mabugu (2008), on the other hand, found that the output of some agricultural commodities (i.e., grains, beans, vegetables, livestock, and forestry) would experience a modest increase under the FTLRP if the reform is well managed using a computable general equilibrium model.

With a few exceptions (e.g., Carberry et al. 2013; Ndlovu et al. 2014; Mango et al. 2015), only limited attention has been paid to the technical efficiency of maize production in Zimbabwe after the FLRTP. Maize is the staple crop in Zimbabwe and is used for both household consumption and income generation. In recent years, maize production in Zimbabwe has steadily declined. Data from

[3]For instance, the offer letter given to the A1 farmers explicitly states that the government may withdraw the offer at any time without compensating the farmers for any improvements they made on the land; this provision could disincentive A1 farmers from making investment on the land (Matondi 2012).

the Food and Agriculture Organization (FAO 2018) suggest that Zimbabwe was a net exporter of maize prior to 2001, with the average annual net export exceeding 250 thousand tons in 1961–2001 but has been a net importer since.[4] In 2016, Zimbabwe imported over 800 thousand tons of maize, an amount almost equal to its total domestic production (FAO 2018). Like other agricultural commodities, one possible contributor to Zimbabwe's maize output decline is the 2000 FTLRP, which has resulted in a significant number of smallholder farms lacking the skills and ability to efficiently produce agricultural commodities compared to the previously large-scale commercial farms.

Among papers that focused on maize in Zimbabwe, Ndlovu et al. (2014) compared the efficiency of maize production under conservation versus conventional agriculture, finding that though the farmers in conservation agriculture showed significantly higher yield due to technical progress, there is no statistical difference in the technical efficiency of maize production between the two types of farmers. Carberry et al. (2013) use crop simulation models to determine shortfalls from the maximum attainable yield based on existing levels of agricultural inputs, finding that only 28% of the maize farmers had a technical efficiency over 0.8, and only 45% had an efficiency score over 0.5. Mango et al. (2015), a study closely related to the present paper, estimated that the average efficiency of smallholder maize farmers in Zimbabwe could be improved by 35% if the existing resources and technology are better used. With regard to the factors considered, they found that the gender of the household head, household size, frequency of extension visits, farm size and farm region significantly affected technical efficiency.

The objective of this paper is to contribute to the discussion on the technical efficiency of smallholder maize farming in Zimbabwe after the FTLRP. In particular, I aim to address the following

[4]Data from the World Bank (2018) and other sources suggest similar patterns for Zimbabwe's maize imports and exports.

questions: 1) are land, labor and capital significant in explaining maize production among smallholder farmers; 2) are smallholder farmers efficiently producing maize and if not, how much more output can be achieved with available resources; 3) what are the determinants of technical efficiency in maize production among smallholder farmers in Zimbabwe? Despite the work by Mango et al. (2015) and others, information on maize production efficiency in Zimbabwe, especially after the implementation of FTLRP, remains limited. Given the importance of maize in the country's agricultural sector and the overall economy, answering these questions could provide additional information to decision makers in both the government and international agencies interested in designing programs to increase the country's maize output, enhance farm household income, improve food security, and reduce poverty. Additionally, results from the paper have broad implications beyond maize production in Zimbabwe as similar questions are likely to exist in other agricultural sectors, as well as in many less-developed countries. Similar views are discussed in Mango et al. (2015) on the importance of additional empirical research in the technical efficiency of smallholder system after the FTLRP.

In the following analysis, I employ a recently developed semiparametric model, as well as the conventional fully parametric stochastic frontier model to evaluate how far maize production of smallholder farmers in Zimbabwe deviates from the efficiency frontier. To identify the determinants of technical (in)efficiency, I further allow both models to depend on household characteristics and other factors related to maize production. The use of these variables is justified by the underlying hypothesis of technical efficiency that farmers with the same production technology and resources may produce different levels of output due to heterogeneous managerial skills. Specific variables used are determined based on previous literature and data availability, which I defer the discussion to the data and results sections. Results suggest that smallholder farmers in Zimbabwe are not efficiently using the available resources when producing maize. While labor, capital, and land all significantly affect the total output, the estimated mean efficiency score ranges between 0.595 and 0.772 for the full sample and falls below 0.75 when only A1 households are used. There clearly exists a great potential for maize farmers to increase the total output by improving the technical efficiency of production. I further find that gender and age of the household head, access to extension services, and activities on other crops significantly affect the technical efficiency of smallholder maize production.

This paper differs from Mango et al. (2015), which also investigated the technical efficiency of maize production in Zimbabwe after FTLRP using frontier analysis and cross-sectional data, mostly on methodological aspects.[5] Mango et al. (2015) used the conventional fully-parametric stochastic frontier model with a Cobb-Douglas production function, which may suffer from model misspecification as discussed in Giannakas, Tran, and Tzouvelekas (2003). The semi-parametric approach I adopt, on the other hand, does not impose a specific production technology in the estimation but selects the most appropriate function based on the data. The two methods also differ in the way factors contributing to technical inefficiency are accounted for in the analysis. In the parametric model, these contextual variables are assumed to affect the total output indirectly by altering the inefficiency term. In the semiparametric model, by contrast, these variables are assumed to affect the conditional expectation structure of the efficiency frontier. Secondly, Mango et al. (2015) do not differentiate between the two types of farmers, i.e., A1 and A2, which could display different technical efficiencies due to heterogeneity in land, capital, and labor inputs. the paper instead accounts for heterogeneous production frontiers for A1 and A2 farms, potentially providing more reliable technical efficiency estimates. Moreover, as noted in the data section, the farm households considered in the analysis present rather different production patterns as compared to those in Mango et al.

[5]While Ndlovu et al. (2014) and Carberry et al. (2013) also discuss maize production efficiency in Zimbabwe, the former focuses on the productivity and efficiency of maize under conservation agriculture, and the latter analyzed the efficiency of maize farmers using crop simulation models without analyzing the factors contributing to the inefficiency.

(2015), allowing the paper to provide additional information on the technical efficiency of smallholder maize production not already covered in the literature.

The remainder of this article is organized as follows. Section 1.2 details the two methods (parametric and semiparametric stochastic frontier models) used for the analysis. Section 1.3 describes the data, and results are presented in Section 1.4. Concluding remarks and policy suggestions are given in Section 1.5.

1.2 Methods

In this section I first briefly describe the parametric stochastic frontier model commonly used for technical efficiency analysis, and then explain in detail the recently developed semiparametric model that relaxes the assumption of fixed production technology and allows the contextual variables to affect the efficiency frontier directly.

1.2.1. Parametric Stochastic Production Frontier Model

In a seminal paper, Farrell (1957) introduced a framework to measure production inefficiency that uses the frontier production function as a benchmark. Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977) independently developed the parametric stochastic frontier approach so that deviations from the production frontier are a result of both technical inefficiency and random disturbance. Equation (1.1) shows the parametric stochastic frontier model assuming a Cobb-Douglas production function:

$$y_i = a + x_i\beta + v_i - u_i, \quad i = 1,\ldots,n, \tag{1.1}$$

where y_i is the output (on log) by unit i, x_i is a vector of input variables (on log) and a and β are the parameters to be estimated. The error term consists of two elements: v measures the idiosyncratic disturbance due to measurement errors and represents the classical noise, and u measures a one-sided disturbance that captures technical inefficiency ($u_i > 0$). The random error term v is assumed to follow a two-sided normal distribution (i.e., $v \sim iid\ N(0,\sigma_v^2)$), while u is distributed half-normally on the non-negative part of the real number line (i.e., $u_i \sim iid\ N^+(0,\sigma_u^2)$). The production function $f(\cdot)$, defining the maximum output that can be achieved given the inputs x, is assumed to be identical for all units i.

To estimate the determinants of technical (in) efficiency, Equation (1.1) is modified to allow the inefficiency term u_i to linearly depend on exogenous (or contextual) variables z_i, as in Equation (1.2):

$$u_i = z_i\delta + w_i, \tag{1.2}$$

where δ is a vector of parameters for the determinants of technical inefficiency, w is the truncation of the $N(0,\sigma_u^2)$ distribution such that $w_i > -z_i\delta$, and u is a non-negative truncation of the $N(z_i\delta,\sigma_u^2)$ distribution (Battese and Coelli 1995). This specification takes into account the heterogeneity of each individual unit by modeling the mean of the inefficiency term as a function of the contextual z variables. As such, it introduces variables into the model that directly affect production efficiency and hence indirectly influence each unit's total output y_i (Lensink and Meesters 2014). As also indicated by Latruffe (2010), these determinants have to be considered in order to generate heterogeneous levels of performance.

Equations (1.1) and (1.2) are often estimated in one-step by maximum likelihood. While it is possible to specify different functional forms for $f(\cdot)$ (e.g., translog), the parametric stochastic frontier model is often criticized for its lack of flexibility in defining the production technology. Giannakas, Tran, and Tzouvelekas (2003) show that not only the estimated technical efficiency depends on the choice of functional specification, but that it may be statistically difficult to select the most appropriate production technology among a set of feasible parametric alternatives. In other words, assuming $f(\cdot)$

to belong to a parametric functional family can be too restrictive and sometimes even inappropriate.

1.2.2. Stochastic Frontier with a Generalized Additive Model (GAM)

To overcome the *a priori* specification of the production technology, Fan, Li, and Weersink (1996) introduce a two-step pseudo-likelihood procedure to estimate the stochastic frontier model where the functional form of the frontier is not known and is obtained via kernel regressions. Specifically, the frontier function can be rewritten as:

$$f(x_i) = E(y_i|x_i) + \phi, \tag{1.3}$$

where $\phi = \sigma_u(2/\pi)^{0.5}$ and $E(y_i|x_i)$ is the conditional expectation of the output that can be consistently estimated by any semi or nonparametric method. The problem of correctly specifying $f(\cdot)$ is therefore equivalent to estimating the conditional expectation of the output $E(y_i|x_i)$.

Following Fan, Li, and Weersink (1996), Vidoli and Ferrara (2015) further extend this approach by considering a Generalized Additive Model (GAM) that explains the variability of the response using an additive function of the inputs as in the corresponding parametric model. Specifically, under GAM the conditional expectation function in equation (1.3) becomes:

$$E(y_i|x_i) = \psi_0 + \sum_{j=1}^{p} \psi_j(x_{ij}) \tag{1.4}$$

where $j = 1,2,...,p$ indicates each input used in the model and the $\psi(\cdot)^0$s are smooth functions standardized so that $E[\psi_j(x_j)] = 0$ (Hastie and Tibshirani 1990). By allowing non-linear dependence between inputs and the output, the GAM specification is likely to improve the overall fit of the model as compared to the fully parametric specification. Additionally, the model remains fairly straightforward to interpret: the partial response function ψ_j plays the same role as β_j in the parametric model (Equation (1.1)) since both explain how the prediction of response varies as x_j changes.

The nonparametric estimators of the unknown functions ψ_j in equation (1.4) have one-dimensional convergence rates (Stone 1986). Since each additive term is estimated using a univariate smoother, the estimators are also able to avoid the *curse of dimensionality* problem commonly present with non-parametric models. The fitted functions ψ_j may help to find suitable simple transformations of the input variables and, where possible, to switch to a parametric specification of the model. Therefore, the GAM model includes the linear parametric model as a special case where $\psi_j(x_j) = \beta_j x_j$ but is more general and flexible. Furthermore, the gradients of the non-parametric model can be interpreted as partial output elasticities and their sum as the elasticity of scale, similar to the parametric model (Henningsen and Kumbhakar 2009).

1.2.3. Allowing Contextual Variables under the GAM Framework-GAMLSS Model

In the parametric analysis, the contextual variables indirectly modify the production process by affecting the technical inefficiency term u_i (equation 1.2). However, as with the production technology, there is no general rule defining how the contextual variables should enter the input/output relationship–they could influence the productivity or technical efficiency or both. Greene (2008) contends that exogenous factors may exert an influence on a producer's performance by directly affecting the production function $f(\cdot)$ itself rather than the efficiency term u with which the production process is operating. The lack of consensus on how exogenous variables should be handled is evidenced by the variety of approaches employed in the empirical literature (e.g., Johnson and Kuosmanen (2011), Florens, Simar, and Van Keilegom (2014) and Mastromarco and Simar (2015)).

Ferrara and Vidoli (2017) recently proposed a new approach to include exogenous factors under the GAM framework by considering the generalized additive models for location, scale and shape (GAMLSS) of Rigby and Stasinopoulos (2005). Specifically, a GAMLSS assumes that the response variable $y \sim D(y;\mu,\omega,\tau,\nu)$ where $D \in \mathrm{D}$ can be any distribution, either continuous or discrete, and the four parameters (μ,ω,τ,ν) are the location (mean), scale (standard deviation), skewness (shape) and kurtosis (shape) of the distribution, respectively. It is also assumed that D may exhibit heteroskedasticity, i.e., the scale or shape of the distribution of the response may change with explanatory variables. For stochastic frontier models, since the normality assumption is typically assumed in the analysis, it is therefore relevant to specify the mean (μ) and scale (ω) of the distribution. Based on these assumptions, equation (1.1) under the GAM framework that allows for external factors can be re-written as:

$$y_i = \Psi(x_i;z_i) + v_i - u_i, \qquad i = 1,\ldots,n, \tag{1.5}$$

where the input variables x specifies the conditional expectation μ and the z variables are used as additional explanatory variables for the scale of the distribution (ω). Specifically, I assume

$$\mu = \eta_1 = f_1(x), \tag{1.6}$$

$$\omega = \eta_2 = f_2(z). \tag{1.7}$$

where $f_1(\cdot)$ and $f_2(\cdot)$ are generic functions and each parameter of the distributions can be modeled as linear/nonlinear parametric functions and/or smoothing functions of the explanatory variables (e.g., cubic splines, penalized splines, lowess) and/or random disturbances. In essence, this approach assumes that instead of directly influencing individual technical (in)efficiency, the exogenous variables affect the total output by modifying the conditional expectation structure of the frontier. It should be noted that a special case under this specification is that the input variables x and contextual variables z only linearly affect the total output. The proposed pseudo-likelihood estimators allow flexibility in model selection and capability of imposing monotonicity constraints between each input and the corresponding output. The latter property can be imposed using P-spline (Eilers and Marx 1996) for the nonparametric modeling of the relevant GAM as illustrated in Bollaerts, Eilers, and Aerts (2006) and Muggeo and Ferrara (2008).

The GAMLSS model for stochastic frontier analysis in equations (1.5)-(1.7) can be estimated in two steps[6].

- estimating the conditional expectation $E(Y \mid X = x, Z = z)$ (*i.e.* the "mean" frontier) *via* GAMLSS,
- estimating error term parameters (σ_v, σ_u) by pseudo-likelihood estimators of Fan, Li, and Weersink (1996).

Under the GAMLSS framework, the technical efficiency score of each unit can be estimated by deriving the conditional distribution of the component u with respect to the compound error $\varepsilon = v - u$ (Jondrow et al. 1982), which may further be written as:

$$TE_i = \exp\{-\hat{u}_i\}. \tag{1.8}$$

T-tests can be used to determine whether a specific coefficient of the contextual variables is statistically significant. Additionally, χ^2 test or likelihood ratio test (*LRT*) can be used to compare the change in global deviance to evaluate the statistical significance of anynonlinear term in the GAMLSS framework.

Since there is no 'best' approach for efficiency analysis in the presence of contextual variables,

[6] A detailed description of the estimation procedure is available in Ferrara and Vidoli (2017).

I will employ both methods, namely the parametric model of Battese and Coelli (1995), which I refer to as SFA-BC, and the recently-developed semiparametric model of Ferrara and Vidoli (2017), or SFA-GAMLSS to estimate the technical efficiency of maize production in Zimbabwe.[7] The two models differ in their ability to take into account observable heterogeneity and hence, a comparison of the two allows us to evaluate the effect of controlling for different kinds of heterogeneity on the efficiency estimates and check the robustness of the alternative model.

1.3 Data

A survey was conducted in 2014 in three farms (Long Croft, Sweet Valley, and Davaar) in the Mazowe district of the Mashonaland Central province in Zimbabwe. Located near Harare (the capital city of Zimbabwe, which is also a gateway to international markets), Mazowe is comprised primarily of undulating terrain particularly suitable for agricultural production thanks to its largely flat land, fertile soils, and plentiful rainfall. According to Chiweshe, Chakona, and Helliker (2015), agricultural production in the region is characterized by highly contested new land tenure arrangements, as well as a rapid pace of land acquisition/redistribution under various resettlement programs. Wiggins (2016) reported that under the FTLRP, the population of Mazowe grew rapidly by 22% from 2002 to 2012 due to the influx of farmers resettled on former large-scale commercial farms. Because of its large agricultural output and heavy influence from government resettlement programs, Mazowe appears to be an ideal region to evaluate the agricultural production efficiency in Zimbabwe under the FLTRP.[8]

The three farms surveyed are in the same agricultural geographical typological area in the

[7]The parametric and semiparametric models described in this section can be estimated using the R Environment (R: A language and environment for statistical computing 2017) by exploiting the following packages: frontier (Coelli and Henningsen 2013), semsfa (Ferrara and Vidoli 2015) and gamlss (Stasinopoulos and Rigby 2007).
[8]As pointed out by one reviewer, the study focuses on Mazowe district, one of the most productive Maize production regions in Zimbabwe. The analysis presented here is therefore limited in scope as it cannot represent the full picture of Maize production in Zimbabwe given the heterogeneity presented across the country.

Mazowe district. The sample consists of a total of 113 A1 households who owns less than 10 hectares of land and 63 A2 households that owns more than 10 hectares of land. For both types of farmers, information collected through questionnaires includes household characteristics, maize output realized, inputs (land, capital, and labor) used for maize production and access to extension services. The questionnaire also includes information on the type of other crops grown and the cost to produce these crops for A1 households.[9]

Table 1 shows the summary statistics of maize production and household characteristics for both A1 and A2 farms in the sample. A2 farmers on average allocated a larger land area, used more capital and devoted more labor for maize production as compared to A1 farmers.[10] While A2 farmers are able to generate a higher per hectare output, the yield difference between the two types of farms is not statistically significant. Both A1 and A2 farmers in the sample on average produced maize at over 2,000 kg/hectare, which is remarkably higher than the average maize yield of 930 kg/hectare in Zimbabwe in 2014 (FAO 2018).[11] While the Mazowe district clearly is more productive compared to the rest of Zimbabwe, its yield remains significantly lower than the average maize yield in Southern Africa (4,762 kg/hectare) and the world (5,622 kg/hectare) in 2014 (FAO 2018), suggesting much room for improvement in maize production.

Per-hectare capital and labor used for maize production are again slightly higher for A2 farms. Under the FTLRP, the government could withdraw the land offer to A1 farms without compensating the beneficiaries for their capital investment to the land. This provision, however, does not apply to A2 farms – the government in fact would provide compensation for A2 farms should they decide to

[9]These data for A2 farmers were not collected in the survey.
[10]Recall that A1 farmers are typically only equipped with less than 10 hectares of land, while A2 farmers often own over 10 hectares of total land.
[11]In the subsequent two years the average maize yield in Zimbabwe had further dropped to below 650 kg/hectare FAO (2018).

withdraw the land offer. This may explain the slightly higher per hectare capital and labor A2 farmers used for maize production than their A1 counterparts, which further contributes to the higher maize yield achieved by these farmers.

Table 1. Summary Statistics of Data for Maize Production Efficiency Analysis.

	A1 (N ¼ 113)		A2 (N ¼ 63)		
	Mean	Std Dev	Mean	Std Dev	t-stat
Maize production					
Total output (kg)	6,172.16	(3,996.40)	12,128.70	(7,552.32)	−5.78***
Land used (hectare)	2.92	(1.45)	5.50	(2.70)	−6.96***
Yield (kg/hectare)	2,073.88	(651.27)	2,149.81	(586.95)	−0.79
Capital used (Z$)	982.82	(614.61)	1,954.65	(1,191.64)	−6.00***
Capital per hectare (Z$)	353.26	(182.77)	373.08	(187.99)	−0.67
Labor used (hours)	217.42	(112.61)	431.71	(223.53)	−7.07***
Labor per hectare (hours)	76.19	(21.23)	79.78	(23.16)	−1.01
Household characteristics					
Age of household head	56.34	(12.77)	57.12	(12.59)	−1.17
Gender of household head					
Male	80		46		
Female	33		17		
Access to extension service					
Yes	83		45		
No	30		18		
Farmland information					
Total farmland area	6.25	(0.98)			
% of area for maize	47.00	(22.58)			

T-stats are calculated for the difference in mean between A1 and A2 farms.

*Signif. codes: *** p<0.01, ** p<0.05, * p<0.1.*

Maize production in the sample appears to be volatile. As evidenced by columns 3 and 5 of Table 1, almost all variables associated with maize production have large standard deviations. Since all farmers covered in the analysis are located in the same agricultural geographical area and the crops grown are subject to similar weather disturbances and other random shocks, the large differences in maize production indicate a high degree of heterogeneity among farmers depending on individual farm household's ability in utilizing available resources.

Table 1 shows rather comparable household characteristics for the two types of farmers. Most of the households are male headed (over 70%) with the average age of the household head above 55 years. Additionally, over 70% of the families have access to extension services, though it does not imply that these farmers received extension services.[12] The last two rows of Table 1 show the total land area used for other crop production. This information is only available for A1 farms. A variety of other crops are grown in the region, including soya beans, cotton, sorghum, groundnuts, sugar beans, sunflower, etc. Some farmland is also set aside for fallow. On average, A1 households in the sample occupied 6.25 hectares of farmland, of which 47% were used for maize production. The second most popular crop is soya beans, accounting for 24% of the farmland.

The household characteristics and other crop variables are used as contextual variables to determine the factors affecting technical (in)efficiency of maize production among smallholder farmers in Zimbabwe. These variables are selected based on a joint consideration of previous literature and data availability. Age of the household is often considered affecting agricultural decisions (Chirwa 2007; Langyintuo and Mulugetta 2005; Mango et al. 2015), as older farmers tend to rely more on experience rather than technology and are sometimes unwilling to accept the newer management practices. Gender of the household head is also considered to affect agricultural production due to bias placed on women (Abdulai, Nkegbe, and Donkoh 2013; Alene and Manyong 2008; Mango et al. 2015). Previous literature also suggests that access to extension activities can significantly increase technical efficiency (Birkhaeuser, Evenson, and Feder 1991; Mango et al. 2015; Owens, Hoddinott, and Kinsey 2003), and that crop diversification can as well affect shortfalls from the production frontier (Manjunatha et al. 2013; Solís, Bravo-Ureta, and Quiroga 2009).

[12]I also collected the education background of household head. However, there is little variability with the education variable since most of the household head only received secondary education.

Compared to Mango et al. (2015), the households in the sample devoted significantly more land for maize production–the average maize area is 0.892 hectares in their study while here, the acreage maize area is 2.92 and 5.5 hectares for A1 and A2 farms, respectively. The farmers in the present paper also had a higher yield (about 2,000 kg/ha) compared to in Mango et al. (2015) (about 1,400 kg/ha). The differences in maize production characteristics in the two studies suggest that the paper complements the work by Mango et al. (2015), providing further insights into the technical efficiency of smallholder maize production after the FTLRP in Zimbabwe.

1.4 Results

The two models presented in Section 1.2 are applied to the maize production data I collected. The quantity of maize produced (y), as well as all inputs (i.e., labor, capital, and land) are converted to their logarithmic values. I first analyze the technical efficiency of A1 farmers and then estimate the two models by considering both types of farmers.[13] Pooling across the two types of farmers is justified given the comparable levels of yield, labor and capital investment per hectare and household characteristics for A1 and A2 farmers as shown in Table 1.

Prior to the estimation, I first test the adequacy of the Cobb-Douglas function as compared to the corresponding translog specification in the full parametric model (SFA-BC). Results based on the Wald test (F ¼ 1:30, p ¼ 0:27) and the likelihood ratio test (χ2 ¼ 8:26, p ¼ 0:22) suggest that the translog specification fails to provide additional information on the relationship between the output and input variables.[14] As a result, I proceed with the more parsimonious Cobb-Douglas specification

[13]There are 113 A1 farmers and only 63 A2 households. I find the models perform poorly when applied to A2 farmers alone, perhaps due to the small sample size.

[14]Since the translog model nests the Cobb-Douglas specification, I can use the Wald and the likelihood ratio tests to determine whether the former provides a better fit than the latter, more parsimonious model.

for the SFA-BC model. The SFA-GAMLSS model is estimated by imposing the monotonicity constraint for the inputs under the p-splines framework, and likelihood ratio tests (LRT) are used to evaluate the statistical significance of anynonlinear term.

1.4.1. Results for A1 Sub-Sample

Estimation results using A1 households alone are reported in Table 2. Both models suggest that all three inputs, namely, land, labor, and capital, are significant in explaining the total output. The parametric model (SFA-BC) indicates increasing returns to scale as evidenced by the larger than unity of the sum of the three estimated coefficients (0.483 + 0.552 + 0.128 = 1.163). The elasticity of maize production is the highest with respect to labor (0.552), followed by land (0.483) and capital (0.128).

Table 2: Stochastic Frontier Model Estimation Results for A1 Farm Households.

	SFA-BC			SFA-GAMLSS		
	Est	SE	Pr(>|z|)	LRT/Est	SE	Pr(Chi)/Pr(>|t|)
Production function						
Intercept	4.639	0.597	0.000***	8.544	0.021	0.000***
Land	0.483	0.129	0.000***	138.091		0.000***
Labor	0.552	0.127	0.000***	158.592		0.000***
Capital	0.128	0.062	0.038**	74.118		0.000***
	Est	SE	Pr(>|z|)	Est	SE	Pr(>|t|)
Contextual variables						
Intercept	0.331	0.349	0.343	−1.571	0.375	0.000***
Male	−0.145	0.105	0.168	−0.295	0.156	0.062*
Age	0.004	0.004	0.302	0.009	0.004	0.101
Extension	−0.299	0.140	0.033**	−0.548	0.162	0.001***
Other crops	−0.002	0.032	0.959	0.093	0.045	0.040**
Λ	3.404			2.109		

*Signif. codes: *** p<0.01, ** p<0.05, * p<0.1.*

For the semiparametric model (SFA-GAMLSS), the gradients of the dependent variable (logarithmic output quantity) with respect to the explanatory variables (logarithmic input quantities) can be interpreted as partial output elasticities. Unlike the SFA-BC model, the semiparametric specification allows (marginal) effects of the explanatory variables to differ between observations without being restricted by an arbitrarily chosen functional form (Czekaj and Henningsen 2012).[15] These observation-specific output elasticities are reported in Figure 1.

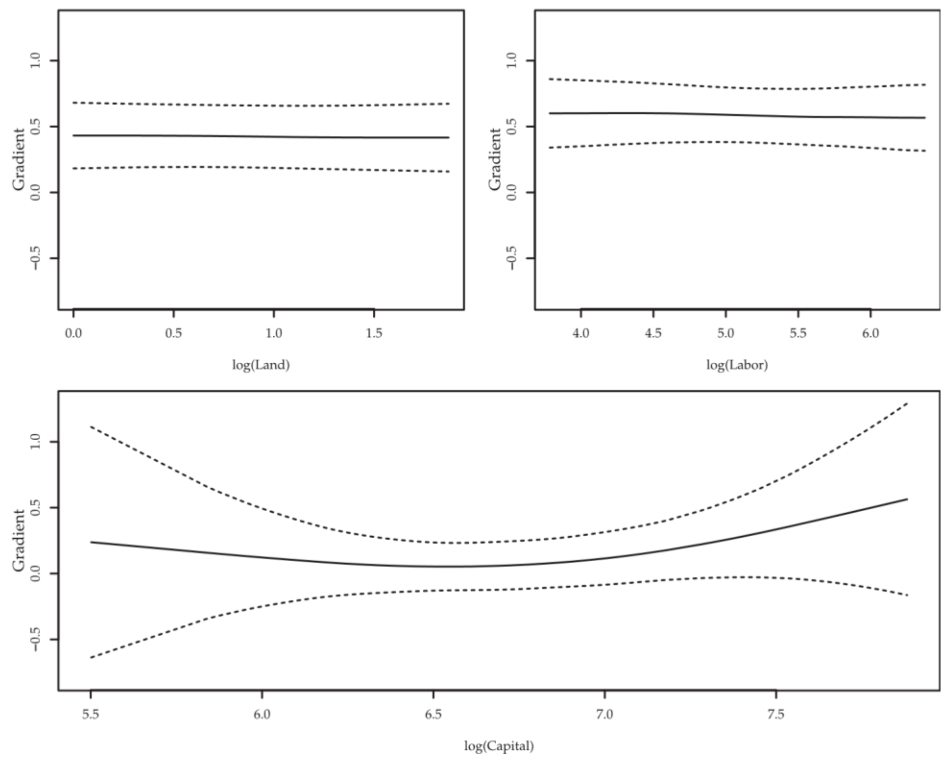

Figure 1: Gradients (output elasticities) estimated by the semiparametric model for various input levels.

As can be seen in the figure, the estimated output elasticities with respect to land and labor fluctuate around the corresponding parameter estimated by the SFA-BC model, while I observe much more heterogeneity for output elasticity with respect to capital. Based on these individual elasticities, I report the returns to scale implied by the semiparametric model and its relation to the output, as in Figure 2. Consistent with the parametric model, all farms operate under increasing returns to scale, with the majority of returns to scales ranging between 1.05 and 1.3. Additionally, there exists a U-shaped relationship between output and returns to scale – farms producing around the median may

[15]In other words, farms can adopt different production technologies and as a result, observation-specific measures of the production technology may be estimated.

gain less from increasing inputs compared to the rest of farms.

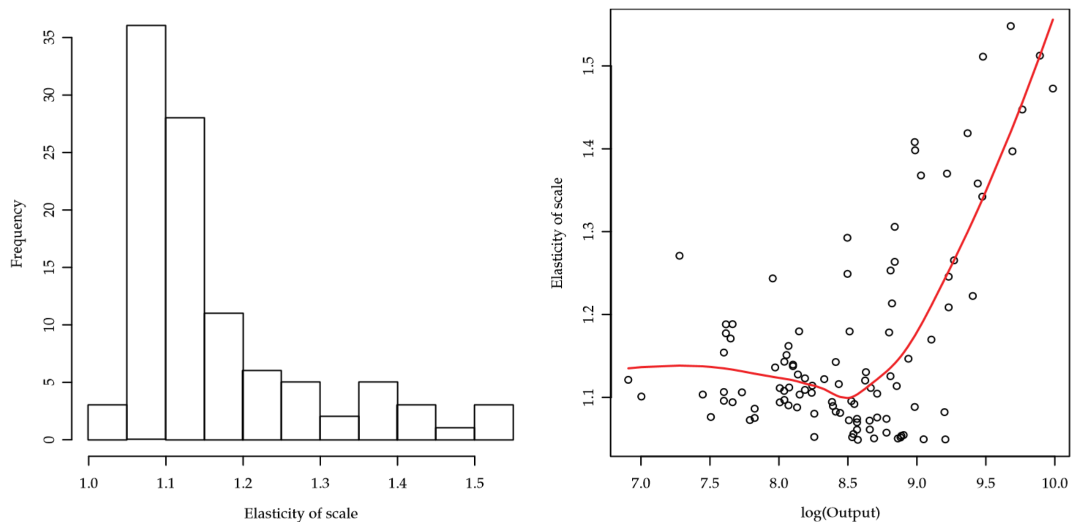

Figure 2: Elasticities of scale and relationship with farm size obtained by the semiparametric model.

Turning next to the factors affecting technical efficiency, I can see that the SFA-GAMLSS highlights greater statistical significance for all coefficient estimates. In the case of the SFA-BC, only the extension service variable is statistically significant in explaining the mean of the technical inefficiency (u). By contrast, all contextual variables are significant in the SFA-GAMLSS, though with differing levels of statistical significance. With the exception of the intercept and the dummy variable for other crop areas, the signs of other contextual variables are consistent across two specifications. Overall, the results given by the semiparametric specification are coherent with the relevant literature, which I discuss below.

First, households with an older household head are on average less efficient, perhaps because they are in general more conservative than their younger counterparts. Younger farmers should be more inclined to adopt new management practices that are able to use the available resources more efficiently (Chirwa 2007; Langyintuo and Mulugetta 2005). Older farmers, on the other hand, may rely more on their experience with the current technology and are slow in adapting to the newer, more efficient practices.

Second, male-headed households appear to be more efficient than female-headed households. A large volume of literature has documented the cultural or social biases (e.g., customs, traditions, religious beliefs, social norms, etc.) against women that have led to an asymmetric distribution of resources and responsibilities, especially in less developed countries (Alene and Manyong 2008; Abdulai, Nkegbe, and Donkoh 2013). These biases not only place restrictions on women's activities but also limit their ability to access new information and technologies, weakening their technical efficiency in agricultural production as compared to male farmers. Additionally, Doss (2001) concluded that based on evidence from 25 years of literature on agricultural production in Africa, female farmers are often not contacted by extension services even if they have access to such services, further lowering their production efficiency.

Households who have access to extension services are more efficient in maize production. Indeed, extension services not only provide the platform for acquiring new information that promotes technology adoption, but also reduce the negative effect due to a lack of formal education in the overall decision to adopt new technologies. Owens, Hoddinott, and Kinsey (2003) found that access to extension services raised farm production by about 15% in resettlement areas of Zimbabwe. Birkhaeuser, Evenson, and Feder (1991) show that contact with extension services could raise farm efficiency by as high as 27%. the results suggest that among all variables considered, access to extension services have the largest impact on technical efficiency.

Additionally, the results from SFA-GAMLSS suggest that working with other types of crops reduces the technical efficiency of maize production for A1 households. While crop diversification is often associated with traditional benefits such as increased farm resilience and higher spatial and temporal biodiversity, it may be difficult for smallholder farmers to achieve a high yield when engaging in multiple-crop production due to the lack of ability in efficiently managing multiple crops. However, the magnitude of this effect is relatively small compared to other contextual variables.

Efficiency scores implied from the two models are reported in Figure 3. Mean efficiency is 0.746 for the semiparametric model and 0.738 for the parametric model. The distributions of the efficiency scores from the two specifications bear a close resemblance. These results are confirmed by the high Spearman and Kendall correlation coefficients between the efficiency scores from the two models, which are equal to 0.927 and 0.777, respectively.

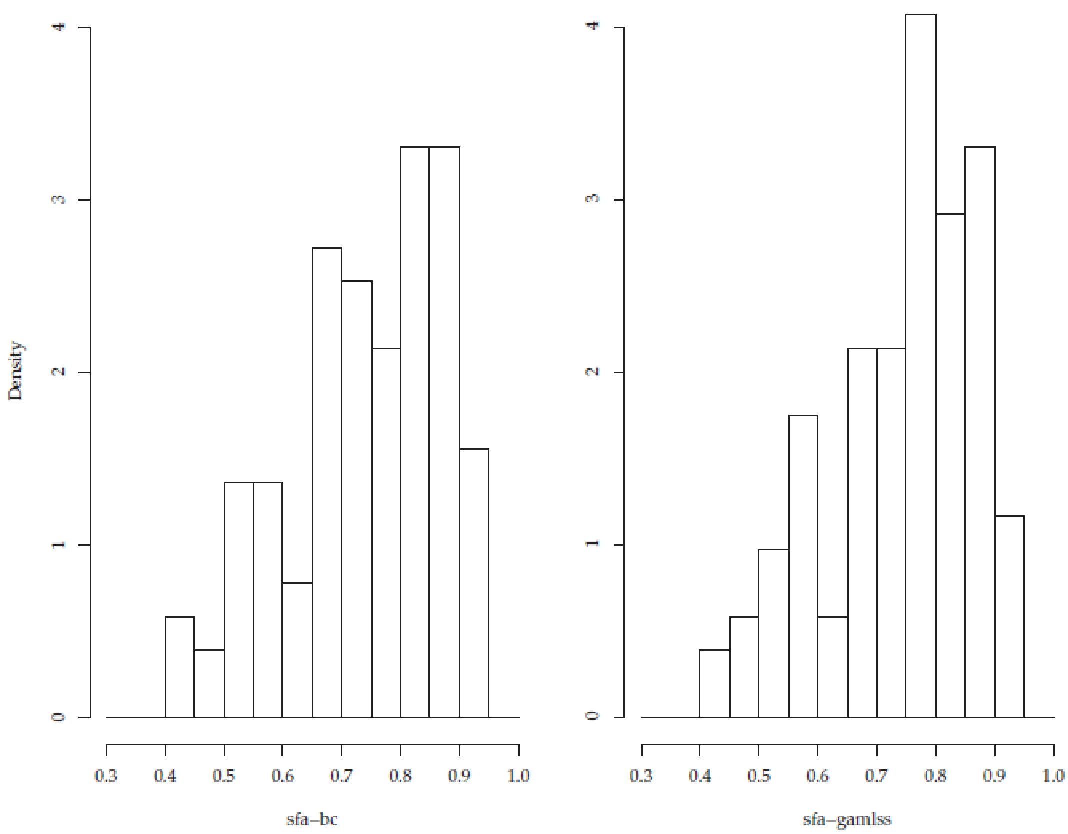

Figure 3: Efficiency score for the two model competitors for A1 farmers: parametric (SFA-BC) and semiparametric (SFA-GAMLSS).

To better understand the results, I analyze the λ parameter which represents the relative variability between the technical inefficiency and the random error, i.e., the relative contribution of v and u on ε (Kumbhakar and Lovell 2000). If $\lambda \rightarrow 0$, the model excludes the presence of technical inefficiency and on the other hand, the stochastic frontier model degenerates into a Deterministic Frontier Analysis (DFA) type if $\lambda \rightarrow +\infty$, (Aigner and Chu 1968), where every departure from the frontier is due only to technical inefficiency. For the SFA-BC (parametric) model I find that $\lambda = 3.404$ while for the SFA-GAMLSS (semiparametric) model $\lambda = 2.109$, both suggesting the greater importance of technical inefficiency than random disturbances in production shortfalls from the frontier. The higher value of λ in the SFA-BC model can be explained by the fact that the semiparametric model captures more variability associated to the inputs and to the contextual variables in the conditional expectation structure of the frontier.

1.4.2. Full Sample Analysis using both A1 and A2 Households

Next I consider the full sample that includes both A1 and A2 farmers. I estimate the same models as those specified and reported in Table 2 except for excluding 'otherarea' variable in the technical efficiency equation and adding a dummy variable indicating the type of farmers (A1 = 1) in the mean equation. Results are reported in Table 3.

As can be seen in Table 3, with the only exceptions of the type of farms and capital investment the semiparametric and fully parametric models highlight similar statistical significance for all other coefficient estimates. Estimation results suggest that A1 farmers have a slightly lower mean. output as compared to A2 households, and this difference is statistically significant in the SFA-GAMLSS model. With regard to the contextual variables, I find that access to extension services is the only factor statistically significant for both models. The λ for SFA-BC is close to the boundary of the parameter space, which may be attributable to model misspecification or again, to a less flexible specification in the production function.

Table 3: Estimation Results for A1 and A2 Farm Households.

	SFA-BC			SFA-GAMLSS		
Production function	Est	SE	Pr(>|z|)	LRT/Est	SE	Pr(Chi)/Pr(>|t|)
Intercept	5.389	0.392	0.000***	8.832	0.024	0.000***
Type ($A1$ = 1)	-0.053	0.047	0.254	-0.088	0.040	0.028**
Land	0.579	0.083	0.000***	295.701		0.000***
Labor	0.499	0.076	0.000***	298.643		0.000***
Capital	0.077	0.049	0.114	156.732		0.000***
Contextual variables						
Est		SE	Pr(>|z|)	Est	SE	Pr(>|t|)
Intercept	0.569	0.117	0.000***	-1.177	0.274	0.000***
Male	-0.085	0.063	0.176	-0.051	0.123	0.677
Age	0.003	0.002	0.162	0.002	0.004	0.689
Extension	-0.168	0.057	0.003**	-0.353	0.124	0.005**
λ	1e+08			1.699		

*Signif. codes: *** p<0.01, ** p<0.05, * p<0.1.*

The estimated gradients of the dependent variable with respect to each explanatory variable for the semiparametric model are reported in Figure 4. As in the sub-sample analysis for A1 farms, I observe much more heterogeneity for output elasticity with respect to capital, and that all farms operate under increasing returns to scale with most farms having an elasticity of scale around 1.1. Unlike the sub-sample analysis of A1 farms, efficiency scores generated from the two models for the full sample are quite different – the mean efficiency scores are 0.772 and 0.595 for the SFA-GAMLSS and SFA-BC, respectively. The disparity can be partly attributed to the different statistical significances associated with the type of farm and the capital investment variables in the mean equation in the two models. The higher efficiency scores generated from the SFA-GAMLSS specification may also be a result of its ability to accommodate heterogeneous technologies when estimating the mean equation as compared to the fully parametric model.

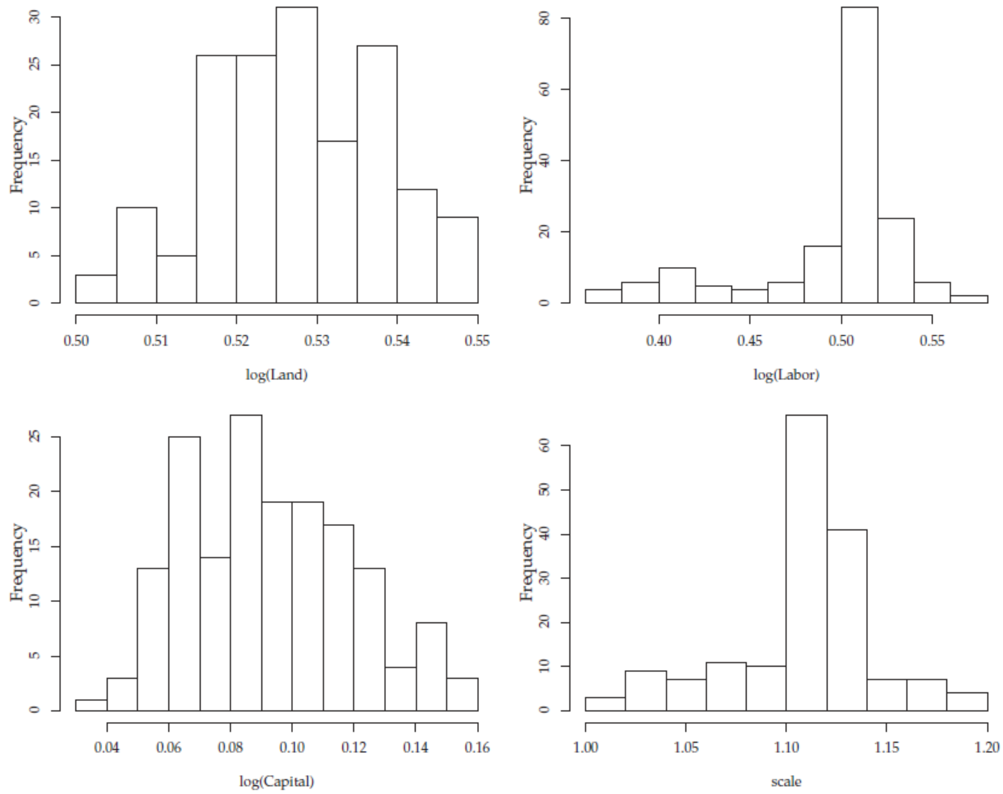

Figure 4: Output elasticities and elasticities of scale from semiparametric models.

Finally, I plot in Figure 5 the technical efficiency score for each household against their maize output based on the estimation results from both models. As can be seen, the level of technical efficiency tends to rise as the output increases, suggesting the need to increase inputs for maize production so that higher efficiency can be reached. All in all, the analysis produced some interesting results regarding the technical efficiency of smallholder maize production in Zimbabwe. The estimated mean technical efficiency score I obtained appears to be higher than in both Mango et al. (2015) and Ndlovu et al. (2014), who found the efficiency level to be around 0.65 and 0.68, respectively.

A possible contributor to the discrepancies is the use of different study areas – while Mazowe, one of the most productive areas for maize production in Zimbabwe, is considered in the present study, the other two studies analyzed regions with less productive areas.

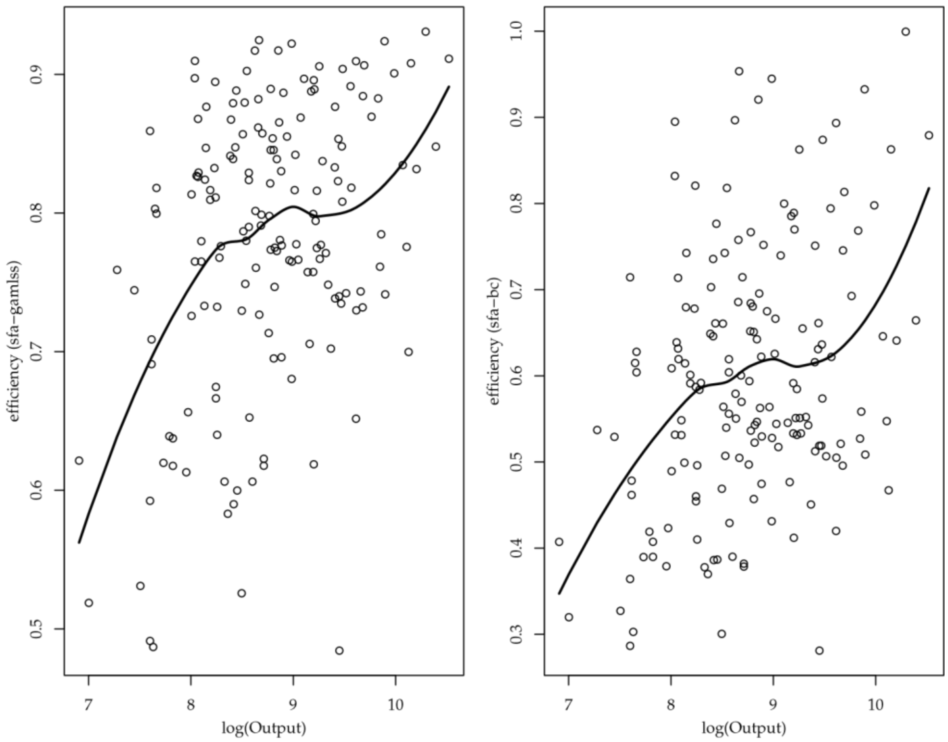

Figure 5: Efficiency estimated by semiparametric and parametric models against log(output).

Findings from this paper may, therefore, be considered an upper-bound for maize production technical efficiency in Zimbabwe. Regardless, the results are consistent with previous studies that there exists a high level of technical inefficiency in Zimbabwe among smallholder maize producers after the implementation of the FTLRP. For comparison, Seyoum, Battese, and Fleming (1998) reported that the mean technical efficiency score for maize producers in Ethiopia is 0.866. Tchale and Sauer (2007) report that the efficiency of maize production in Malawi is 0.91 for farmers applied integrated soil fertility management and 0.79 for those who did not. In Cameroon, Binam et al. (2004) find the mean technical efficiency of maize production to be 0.75. While these results are clearly dependent upon the specific estimation method and data employed, they nevertheless indicate that the efficiency of maize production in Zimbabwe, especially those from smallholder farmers, could significantly be improved.

1.5 Conclusion

In this study, I evaluate the technical efficiency of maize production among smallholder farmers in Zimbabwe, an important issue as the country moves from large commercial farm agriculture to smallholder production under the Fast Track Land Reform Programme (FTLRP). Specifically, I seek to answer if smallholder farmers are efficiently allocating their land, labor and capital resources when producing maize and what determines variations in efficiency levels after the implementation of the FTLRP, a controversial policy that has caused radical changes in the land tenure system in Zimbabwe. I find that beneficiaries of the FTLRP in Zimbabwe are not efficiently utilizing their available agricultural resources in maize production. The average efficiency level appears to be under 0.75 when only A1 farms are considered. When both types of farmers are included, the average efficiency of maize production among smallholder farmers is 0.772 for the semiparametric specification and 0.595 for the fully parametric model. Among other things considered, gender and age of the household head, access to extension services and activities of other crops significantly affect farmers' efficiency levels. Results suggest a large output improvement potential if the farmers can adopt more advanced management practices and use the available resources more efficiently.

This paper complements existing studies on the technical efficiency of maize production in Zimbabwe after the implementation of FTLRP, providing additional insights into ways that can raise maize productivity that has fallen rapidly over the past decade. From a methodological point of view, the semiparametric stochastic frontier production model employed in the present analysis represents a significant improvement over the fully parametric stochastic frontier models commonly used in agricultural technical efficiency analyses (e.g., Mango et al. 2015). The SFA-GAMLSS specification not only allows for flexible production functions, but also assumes that exogenous variables affect the individual output by affecting the conditional expectation structure of the production frontier. Since the true form of the frontier is rarely known and in practice, it is impossible to measure how well any chosen functional form approximates the true production function, the semiparametric model could allow a more precise estimation of the frontier. Additionally, the failure to model the exogenous factors in the conditional mean equation as in Battese and Coelli (1995) may lead to biased estimation of the production frontier model and the level of technical inefficiency.

This paper points to the importance of developing conducive policies to encourage investment in maize production as both types of farmers demonstrate increasing returns to scale. Policies should be made to allow for easy access to key inputs such as fertilizers and machinery, as well as agricultural credits to allow further investment. Additionally, securing the land tenure system could also greatly increase the total output as smallholder farmers may be reluctant to make land conservation or other capital and labor investments under the current land redistribution policy. The resulting agricultural intensification can further improve maize production efficiency as supported by the positive relationship between the technical efficiency score and the level of output found by both semiparametric and fully parametric models.

Given the significant role of extension services in lowering technical inefficiency, there is a great need to expand extension access and encourage more extension visits to farmers. Extension services only help farmers make better use of existing resources by improving their management skills but may also increase the output by encouraging farmers to devote more capital and labor for maize production. the analysis also points to the need for implementing innovative extension practices based on a gender equitable approach. Jiggins, Samanta, and Olawoye (1997) noted that providing female farmers access to extension services not only improves these farmers' agricultural output, but also boosts the efficiency of the overall agricultural sector and enhance the national food security. Some previous studies reported evidence of a diminishing gap between female and male-headed households when the extension service agents employ a large number of women extension agents Alene and

Manyong (2008). Results of the present study suggest that policymakers should aim to reduce gender gaps, to increase access to agricultural advisory services, and to stimulate younger household in agricultural production since they may be more open to new management practices.

Although improving technical efficiency could boost maize output in Zimbabwe, it is also critically important for the government and other international organizations to invest in research and technology development. Productivity growth, as is well established in the literature, can be attributed to both technical change and technical efficiency. While improving technical efficiency can enhance maize output given the existing production technology, technical advances will shift the production frontier outward and increase the total output possible given the existing resources. Policymakers should strive to improve the macroeconomic environment for agricultural production, facilitating technology transfers from developed economies and stimulating research and technology development. Furthermore, a conducive general economic environment also helps attract attracting investment into the agricultural sector, further improving total maize output.

One limitation of the paper is that I only consider the farm households in Mazowe, one of the most productive regions for maize production in Zimbabwe. Given the heterogeneous nature of maize production in the country, results presented in the paper cannot provide the full picture of technical efficiency of smallholder maize system in Zimbabwe. Results obtained in this study may therefore be best considered an upper bound for technical efficiency of maize production in Zimbabwe after the FTLRP. Future study may wish to use a sample representative of the entire Zimbabwean farm households so that a more accurate estimate of technical efficiency may be obtained.

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CHAPTER 2. Elasticity of Substitution and Technical Efficiency: Evidence from US Electricity Generation.

Abstract

The implications of national or regional energy policies for technical efficiency and environmental outcomes in electricity generation depend on fossil fuel input substitution. This study uses state level data to examine fossil fuel (coal and natural gas) substitution in electricity generation under increased availability of natural gas in the United States. I observe that changes in elasticities of substitution from pre-2009 to post-2009 differ across states suggesting that the effects of increased availability of inexpensive natural gas on electricity generation have been spatially heterogeneous. I rely on the observed heterogeneity to assess the effects of fossil fuel input substitution on technical efficiency and CO2 emissions. The results reveal that state level elasticity of substitution between natural gas and coal has a positive effect on technical efficiency and a negative effect on CO2 emissions. Therefore, future policy design and analyses should reflect the implications for regional elasticities of fossil fuel substitution and associated environmental outcomes

Keywords: Elasticity of substitution, electricity, technical efficiency, frontier analysis, natural gas, coal.

JEL CLASSIFICATION: Q3, Q4.

2.1 Introduction

Electricity generation sector has been subject to close regulatory oversight targeting competitiveness of electricity markets, grid access, and environmental quality objectives (Ko and Dahl, 2001). Effectiveness of such policies in part depends on the electric power sector's adjustment in terms of fuel use mix. For example, adjustments in fuel use can influence technical efficiency and carbon emissions in electricity generation, which are often targeted by regulatory programs and policies (Knittel, 2002, EPA 2019). I examine the changes in regional (state) fossil fuel substitution elasticities following increased availability of natural gas from unconventional production in the US. Specifically, I examine the implications of changes in regional elasticities of substitution between coal and natural gas for technical efficiency and carbon emissions.

State-level fuel substitution elasticities in the electricity generation sector are important for policymaking and planning purposes because policies, institutional and regulatory contexts, resource endowments, technology, infrastructure, and the historical development of electric power systems and regulatory policies often differ across states. For example, the Midwestern states in the US historically have had more coal-fired capacity relative to other states (Dahl and Ko, 1998). As a result, fuel consumption and substitution capacities in these states can differ from other states. Environmental regulations, like the renewable portfolio standards (RPS), also differ across states (Maguire and Munasib, 2016; Palmer and Burtraw, 2005). Additionally, electricity market deregulation differences across states led to divergent state level generation technology investment decisions (Csereklyei and Stern, 2018), with corresponding regional implication for fossil fuel input substitutability. While the importance of regional patterns of substitution has been recognized for policy analysis and evaluation (Uri, 1977; Bopp and Costello, 1990; Dahl and Ko, 1998; Gao et al., 2013), state level analysis of substitution has been lacking.

Regional-level substitution among fossil fuels in electricity generation can come from either substitution at individual utilities or substitution across utilities. Substitution at individual utilities occurs either through fuel switching or through adjustments in the queuing order of generation facilities with varying mixes of fuel consumption. Substitution across utilities takes place through bulk transfers of power across utilities within and across regions (Dahl and Ko, 1998). At the state level, such substitution capabilities are subject to regulatory parameters and the availability of appropriate technology, infrastructure, and resources.

Implications for technical efficiency are important to examine because regulatory programs and policies in the electricity generation sector often seek to improve energy generation efficiency. Thermal efficiency-based programs aim to reduce the "heat rate" of generation facilities and thus improve generation efficiency (Knittel, 2002; Joskow and Schmalensee, 1986). For example, recent Environmental Protection Agency's (EPA) Affordable Clean Energy (ACE) rule relies on improvements in heat rates to control emissions of air pollutants from existing generation units (EPA, 2019). Heat rate, or technical efficiency, measures the amount of energy (Btu) used to generate a unit of electricity (kWh). Although the effect of policies and regulations on electric industry performance can be examined in terms of measures like trends in electricity rates, technical productive efficiency measures provide a more straightforward representation of efficiency (Goto and Tsutsui, 2008).

Regulations pertaining to the effects of electricity generation on environmental quality have attracted significant attention from policy makers because the electric power industry is one of the major contributors to greenhouse gas emissions. In the US, electricity production constitutes roughly one-third of greenhouse gas emissions via fossil fuel consumption (EPA, 2014). Consequently, numerous policies have been introduced to improve energy efficiency and/or promote renewable/clean energy development initiatives including but not limited to the Energy Policy Act of 2005, the Climate Action Plan of 2013, the Clean Power Plan (CPP) of 2014, and most recently Affordable Clean Energy (ACE) rule of 2019. In 2015, the EPA finalized the carbon dioxide emission standards for existing and new power plants pursuant to section 111(d) of the Clean Air Act. The guidelines articulated *state-specific* limits in terms of the amount of carbon dioxide emissions per megawatt-hour of net electricity generation, aiming at a 30% reduction in carbon dioxide emissions relative to 2005 levels by 2030. Similarly, in 2019, reversing the guidelines of the CPP, the EPA released the ACE rule where states are responsible for developing respective performance standards that achieve targeted improvements in generation efficiencies at particular types of existing generation units (EPA, 2019).

Changes in fossil fuel supply can have heterogeneous implications for regional electricity generation under constrained shipment capacity. According to the estimates of the US Energy Information Administration (EIA), daily production of dry shale gas in the US increased from 2.5 billion cubic feet in 2002 to 43 billion cubic feet in 2016. The productivity of natural gas wells has been steadily increasing because of ongoing improvements in the precision and efficiency of horizontal drilling and hydraulic fracturing. The increase in natural gas availability has had a significant impact on electricity generation sector.

Since 2008, coal consumption in electricity generation has been declining, while consumption of natural gas has been increasing (Figure 6). These adjustments are not surprising considering the recent increase in the costs of coal-based electricity generation relative to natural gas-based electricity generation (Van Kooten et al., 2013). The growth in the availability of inexpensive natural gas and corresponding adjustments in the electricity generation industry, including infrastructure and generation capacity, have implications for elasticities of fuel substitution. Observing structural beaks in most of the data series in 2009, I examine the differences in fossil fuel substitution elasticities across states pre and post 2009 and evaluate corresponding implications for technical efficiency and CO_2 emissions.

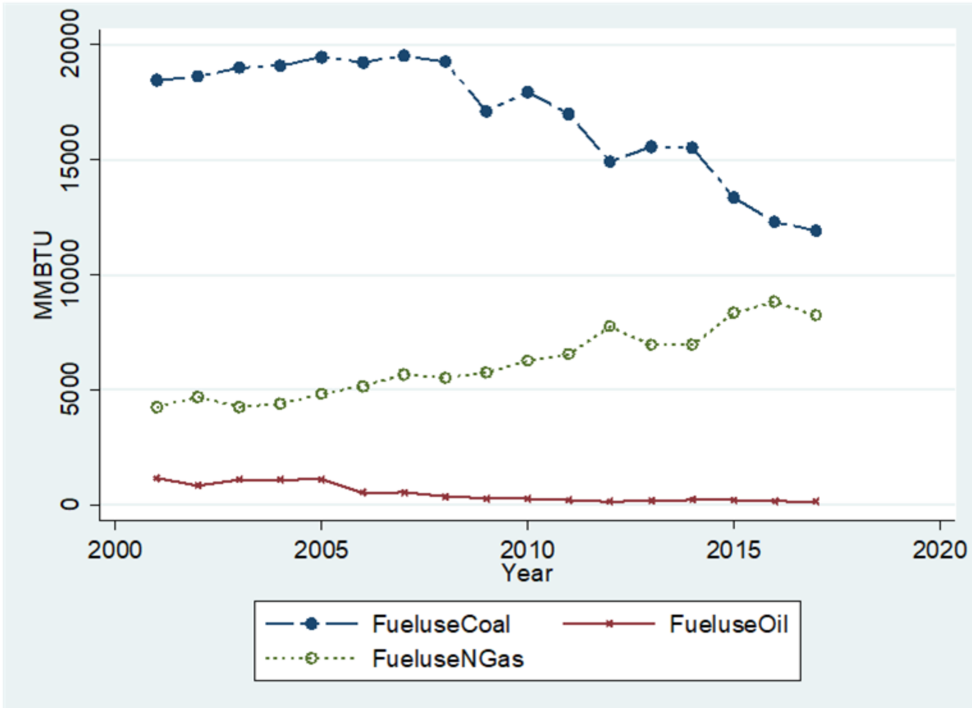

Figure 6. Fuel use for electricity production in the US (Million BTUs)

In this study, I focus on the substitution patterns between coal and natural gas as the primary fossil fuels used in electricity generation. Although the empirical model includes oil-based generation, I focus on coal and natural gas because these fuels represent an overwhelming majority of fossil fuel-based generation. Ramping capabilities of active fossil fuel power plants have significant implications for peaking power generation to meet electricity demand in real-time. Therefore, coal and natural gas substitution patterns are important to consider when evaluating or designing state-level policies intended to influence fossil fuel consumption mix in electricity generation[16].

[16] I reserve the examination of electricity generation from renewable sources for a later study. While renewable and nuclear sources are mainly used for baseload electricity generation, day-to-day fuel substitution comes mostly from fossil fuels subject to technological constraints (Dahl and Ko, 1998). Technological improvements in storage and transmission at some point in time will allow for more flexibility in renewable energy utilization. However, at this time the opportunity for substitution with renewable energy remains limited due to the variable nature of wind and solar energy and due to lack of adequate storage capacity.

2.2 Methodology

First, I use linear panel regression models with shares of coal and natural gas relative to total fossil fuels as functions of prices, electricity generation, and renewable energy policy to describe the changes in fossil fuel consumption in electricity generation at state scale. Next, I quantify the changes in state level elasticities of substitution between coal and natural gas before and after 2009 and examine the corresponding implications for technical efficiency and CO_2 emissions.

2.2.1. Inter-fuel Substitution

Majority of input substitution studies rely on the translog cost function-based approach to quantify elasticities of substitution (Bernstein and Parmeter, 2019; Zhang and Lin, 2019; Jia and Shao 2018; Wesseh and Lin, 2016; Li and Lin, 2016; Shahiduzzaman and Alam, 2014; Ma et al. 2012; Soderholm, 2001; Dahl and Ko, 1998; Griffin, 1977). Limited attention has been given to the examination of inter-fuel substitution at sub-regional scales. Using translog specification of the cost function for electricity generation and associated cost share equations for coal, natural gas, and oil, Gao et al., (2013) studied fuel substitution patterns across seven electricity generation regions in the US based on annual region-level data from 2001 to 2008. They show that natural gas was a substitute input for coal and oil to various degrees across seven electricity generation regions in the US. Similar result was found by Uri (1977). Bopp and Costello, (1990) also used fuel share equations based on translog specification of the cost function to examine elasticities of coal, gas, and oil use nationally and across five regions in the US. They show that regionally explicit estimation is superior to national level modeling in terms of revealing the underlying economics of electricity generation.

I follow prior literature to examine changes in fuel substitution elasticities obtained from a translog specification of the cost function. Given a production function $Y=f(\boldsymbol{X})$, elasticity of substitution, originally introduced by Hicks (1932), measures the change in the relative factor proportion X_i/X_j in response to the change in relative marginal rates of technical substitution f_{Xi}/f_{Xj}

holding output Y constant, where f_{Xi} and f_{Xj} are partial derivatives of the production function with respect to inputs X_i and X_j. Formally, the elasticity of substitution is expressed as $\sigma_{ij} = \frac{d\ln(x_i/x_j)}{d\ln(f_{x_j}/f_{x_i})}$.

In this study, the Allen partial elasticities of substitution, expressed in terms of cost function and its derivatives, are used as $\sigma_{ij} = CC_{ij}/C_iC_j$, where subscripts indicate partial derivatives with respect to prices of inputs, *i* and *j* (Allen, 1938; Uzawa, 1962; Cristensen and Green, 1976; Dasgupta and Roy, 2015).

Following Shephard's Lemma, (1970), cost-minimizing factor demands for a cost function $C = f(P_c, P_{G,}P_o, Y, t)$, are obtained by $x_i^* = \partial C(\mathbf{P}, Y)/\partial P_i$, where $\boldsymbol{P_c}, \boldsymbol{P_{G,}} \boldsymbol{P_o},$ denote prices of coal, natural gas, and oil, respectively, and $i \in \{C, G, O\}$. Alternatively, by logarithmic differentiation, factor cost share equations are $s_i = \partial \ln C(\mathbf{P}, Y)/\partial \ln P_i$ (Christensen and Green, 1976; Berndt and Wood, 1975). Following numerous previous studies, I use translog functional form for the cost function to obtain factor cost share equations and elasticities of substitution (Griffin and Gregory, 1976; Taheri, 1994; Berndt and Wood, 1975; Dahl and Ko, 1998; Ko and Dahl, 2001; Bentzen, 2004; Gao et al., 2013; Linden et al. 2013). The system of the cost function and the corresponding cost-share equations is:

$$ln\,C = \alpha_0 + \sum_i \alpha_i\, ln\,P_i + \alpha_y\, ln\,Y + \frac{1}{2}\alpha_{yy}(ln\,Y)^2 + \sum_i \alpha_{iy}\, ln\,P_i\, ln\,Y + \frac{1}{2}\sum_i \sum_j \alpha_{ij}\, ln\,P_i\, ln\,P_j + (\alpha_t)\,t + \frac{1}{2}\alpha_{tt}t^2 + \alpha_{yt}t\, ln\,Y + \sum_i \alpha_{it}t\, ln\,P_i \quad (2.1)$$

$$S_i = \beta_i + \beta_{iy}\, ln\,Y + \textstyle\sum_j \beta_{ij}\, ln\,P_j + \beta_{it}t \quad (2.2)$$

where C is a vector of state level costs of fossil fuels used in electricity generation over time, S_i is a vector of cost shares of fuel *i* across states and over time, P_i and P_j are vectors of fuel prices across states and over time, and Y is a vector of fossil fuel based electricity generation across states and over time. Assuming that price interaction parameters in the cost share equations are a linear function of state dummy variables (D_s), the share equations are expressed as follows (Gao et al., 2013) with subscript s denoting state.

$$S_{is} = \beta_i + \beta_{iy} \, ln \, Y_s + \sum_j \left(\beta_{oij} + \sum_s \beta_{ijs} D_s\right) ln \, P_{js} \tag{2.3}$$

In accordance with neo-classical production theory, and following extensive prior literature (Linden et al. 2013; Bentzen, 2004; Dahl and Ko, 1998; Ko and Dahl, 2001; Christensen and Green, 1976), parameter restrictions for homogeneity and symmetry conditions are as follows:

$$\sum_i \alpha_i = 1$$

$$\sum_i \alpha_{iy} = 0$$

$$\sum_j \alpha_{ij} = \sum_i \alpha_{ij} = 0$$

$$\alpha_{ij} = \alpha_{ji} = \left(\beta_{oij} + \sum_s \beta_{ijs} D_s\right) = \left(\beta_{oji} + \sum_s \beta_{jis} D_s\right); \; \alpha_i = \beta_i; \; \alpha_{iy} = \beta_{iy}$$

The oil share equation is omitted from the estimation[17]. Following Berndt and Wood (1975), Bentzen (2004), Griffin and Gregory (1976), Bopp and Costello (1990), Dahl and Ko, (1998), and numerous other studies, cost share equations (2.3) are estimated as a system of equations. Natural gas and coal share equations are estimated using seemingly unrelated regression (SUR) for each electricity market region independently using state level data with state and time fixed effects and interaction effects between prices and fixed effects.

[17] Though not necessary for the purposes of this study, the parameter estimates for oil-based fuels can be obtained using homogeneity and symmetry restrictions.

Following prior literature (Dasgupta and Roy, 2015; Linden et al. 2013; Bentzen, 2004; Dahl and Ko, 1998; Griffin and Gregory, 1976; Christensen and Green, 1976), state specific elasticities of substitution are obtained as follows:

$$\sigma_{ijs} = \frac{\left((\beta_{oij}+\sum_s \beta_{ijs} D_s)+S_{is}S_{js}\right)}{(S_{is}S_{js})} \tag{2.4}$$

2.2.2. Technical Efficiency Analysis

Technical inefficiency refers to production taking place in the interior of the production possibility set, i.e., when output falls short of possible attainable level for a given use of inputs (Farrell, 1957). Non-parametric Data Envelopment Analysis (DEA) (Barros and Peypoch, 2008; Pacudan and de Guzman, 2002; Von Hirschhausen et al., 2006) and parametric Stochastic Frontier Analysis (SFA) (Filippini et al., 2004; Goto and Tsutsui, 2008; See and Coelli, 2012; Knittel, 2002; Von Hirschhausen et al., 2006; Hattori, 2002) have been widely used to examine inefficiencies in the electricity industry. Unlike SFA, DEA does not impose a specific functional relationship between inputs and outputs and does not assume specific statistical distribution of the error structure. However, DEA does not account for possible noise in the data and outliers can have a large effect on the result (Bravo-Ureta et al., 2007). On the other hand, SFA models deviations from the frontier in terms of both technical inefficiency and random errors that are outside of individual producers' control. Although DEA and SFA estimates produce remarkably similar conclusions (Von Hirschhausen et al., 2006; Wadud and White, 2000), I use SFA because I am mostly interested in examining the relationship between elasticities of substitution and inefficiencies post frontier estimation. In this respect SFA provides a more convenient framework than mathematical programming-based DEA. Furthermore, while DEA attributes all deviations from the frontier to inefficiencies, SFA factors in inefficiencies as well as random errors.

Earlier work on inefficiency with panel data includes Pitt and Lee, (1981) and Kalirajan, (1991), where the stochastic frontier estimation was based on panel data. Apart from the ability to separate individual and time effects from combined effects in efficiency estimation, the use of panel data also avoids problems related to distributional assumptions as observed in cross section analysis (Schmidt & Sickles, 1984). Fixed effects panel SFA is defined as follows (Greene, 2005; Chen et al., 2014):

$$C_{it} = f(X_{it}\beta).\exp\{\varepsilon_{it}\}; \qquad (2.5)$$
$$\varepsilon_{it} = V_{it} + U_{it};$$
$$V_{it} \sim IID\ N(0, \sigma_v^2);$$
$$U_{it} \sim IID\ N^+(0, \sigma_u^2);$$
$$For\ i = 1,2,3...N;\ t=1,2,3....T$$

where, C_{it} represents the log of cost for the i^{th} state at time *t*. X_{it} is the vector of explanatory variables and β is the associated vector of technology parameters to be estimated. ε_{it} is a composite random error with probability density function $\lambda = {}^{\sigma_u}/_{\sigma_v}$ and $\sigma^2 = \sigma_u{}^2 + \sigma_v{}^2$. V_{it} is the normally distributed random error. U_{it} is the one sided, non-negative and half normally distributed disturbance term that captures inefficiency (Cornwell et al., 1990).

I use translog functional form for the cost function in equation (2.5) (Atkinson & Cornwell, 1994a,b; Filippini et al., 2004; See and Coelli, 2012; Hattori, 2002; Khanna et al., 1999) as defined in equation (2.1) to take advantage of its flexibility and to maintain consistency with estimation of elasticities of substitution[18]. Estimates of inefficiencies obtained from model (2.5) (stage one) are used in the post estimation analysis of inefficiencies according to equation (2.6) (stage two). Inefficiencies U_{it} are expressed in terms of contextual variables (Z), including elasticities of substitution and state characteristics which are not included in the set of production inputs in equation (2.5). The Z variables

[18]Elasticities of substitution are estimated based on regressions for individual electric market regions with respective interactions between prices and state fixed effects to obtain state specific elasticities.

in the inefficiency model may also include input variables specified in the stochastic frontier model, provided the inefficiency effects are stochastic (Battese and Coelli, 1995).

$$U_{it}(Z_{it}, \boldsymbol{\delta}) = \delta_1 Z_{1t} + \delta_2 Z_{2t} + \cdots + \delta_n Z_{nt} + W_{it}; \quad W_{it} \sim IN(0, \omega^2) \quad (2.6)$$

Fixed effects estimation of the stochastic frontier model (2.5) may give inconsistent estimates because the classical stochastic frontier models that use panel data provide no mechanism to separate individual time-invariant unobserved heterogeneity from inefficiency (see Greene, 2005; Chen, Schmidt and Wang, 2014; Belotti and Ilardi, 2017). To this effect, Greene (2005) proposed a true fixed effect regression technique through maximum likelihood estimation (TFE-MLE), which accounts for unmeasured cross-sectional heterogeneity based on the probability density function of the error term (ε_{it}). The TFE-MLE approach made it possible to measure inefficiency and heterogeneity across groups separately. However, the "Incidental parameters problem" in fixed effects specification of the stochastic frontier model can lead to inconsistency (Chen, Schmidt and Wang, 2014; Belotti and Ilardi, 2017). Incidental parameters are "nuisance" parameters that increase as the number of groups in the panel cross-section becomes large. As a result, fixed effects estimation of SFA can be inefficient (Lancaster, 2000; Green 2005).

Chen et al. (2014) provide an alternative approach to address this problem using within-maximum likelihood estimation (WMLE) for the true fixed effects model by exploiting a within-group data transformation. Their maximum likelihood estimation is based only on the joint density of the deviations from means. WMLE approach removes the individual effects by employing the within group data transformation, where deviations from means of every variable in each group are used in the estimation. However, Chen et al. (2014) estimation assumes both, the random white noise and the inefficiency error components, to be homoscedastic. This assumption can affect inference in the SFA framework (Kumbhakar and Lovell, 2000). Belotti and Ilardi (2017) extended Chen et al. (2014) model using first-order autoregressive process to allow for either homoscedastic or heteroskedastic inefficiency. They propose a marginalized maximum simulated likelihood estimation (MMSLE) based on the marginalization of the inefficiency term via simulation. In this approach, first difference estimation is used to eliminate nuisance parameters associated with fixed effects specification. The disadvantage with MMSLE is that model convergence is difficult to attain with high T-dimension (Belotti and Ilardi, 2017). In this study, I use TFE-MLE, WMLE, and MMSLE models for SFA. I estimate TFE-MLE and MMSLE using a one-step procedure (where $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$ are estimated simultaneously combining steps one and two) following Caudill and Ford (1993) and Wang and Schmidt (2002). WMLE is implemented in a two-step procedure to estimate equations (2.5) and (2.6) respectively.

Although the relationship between elasticity of factor substitution and productivity has previously been addressed (Klump and de La Granville 2000), I am not aware of any studies which examine the relationship between technical inefficiencies and elasticities of substitution. Toward this end, I estimate a stochastic frontier distance function to assess the association between inter-fuel substitution and electricity generation inefficiency at the state scale. I am particularly interested in examining the changes in technical efficiency in recent years due to changes in the elasticities of substitution between coal and natural gas.

2.2.3. Inter-Fossil Fuel Substitution and CO_2 Emissions

Next, I evaluate the relationship between interfuel substitution and CO_2 emissions. I estimate a linear panel regression model (equation 2.7) with state (α_i) and time (γ_t) fixed effects to test whether CO_2 emissions respond to changes in elasticity of substitution between coal and natural gas.

$$Y_{it} = \alpha_i + \gamma_t + \beta X_{it} + \varepsilon_{it} \tag{2.7}$$

where; Y is CO_2 emissions, X is a vector of explanatory variables including elasticity of substitution and ε_{it} is the error term for state i and time t. Equation (2.7) estimates the impact of the variation in elasticity of substitution between coal and natural gas, electricity production, renewable portfolio standards and the increase in the availability of natural gas on CO_2 emissions in electricity generation. Point estimates of the state level elasticities of substitution are used as obtained from the systems of equations for each Federal Energy Regulatory Commission (FERC) electricity region.

2.3 Data

The dataset in this study consists of a panel of annual state-level observations from 2001 to 2017, including prices and quantities of fossil fuels used for electricity generation, as well as total electricity generated from fossil fuels. The state-level consumption of coal, natural gas, and oil-based fuels for electricity generation is obtained from EIA (2019a) and is measured in million British thermal units (MMBTU) (Dahl and Ko, 1998). Oil-based fuels include petroleum liquids and petroleum coke aggregated into a single variable representing oil-based fuels measured in MMBTU. State-level total electricity production from coal, natural gas, and/or oil (MWH) across production types (electric generators, commercial and industrial combined heat and power facilities) is obtained from EIA's state level data (EIA, 2019a). State-level prices for coal, natural gas, and oil in the electric power sector ($/MMBTU) are obtained from EIA's SEDS (State Energy Data System) database (EIA, 2019b). Cost shares are computed using state-level fuel prices, respective quantities used in electricity generation, and total expenditures on coal, natural gas, and oil in electricity generation at the state level. Seven states are excluded[19] from the analysis because at least one of the three fuels is not used for electricity

[19] The following states are included in the study Alabama: (AL), Alaska (AK), Arizona (AZ), Arkansas (AR), Colorado (CO), Connecticut (CT), Delaware (DE), Florida (FL), Georgia (GA), Illinois (IL), Indiana (IN), Iowa (IA), Kansas (KS), Kentucky (KY), Louisiana (LA), Maine (ME), Maryland (MD), Massachusetts (MA), Michigan (MI), Minnesota (MN), Mississippi (MS), Missouri (MO), Montana (MT), Nebraska (NE), Nevada (NV), New Hampshire (NH), New Jersey (NJ), New Mexico (NM), New York (NY), North Dakota (ND), Ohio (OH), Oklahoma (OK), Oregon (OR), Pennsylvania (PA), South Carolina (SC), South Dakota (SD), Tennessee (TN), Texas (TX), Virginia (VA), Washington (WA), West Virginia (WV), Wisconsin (WI) and Wyoming (WY). The following states are excluded: Hawaii (HI), Idaho (ID), Rhode

generation, and no prices are available for those fuels. I also include state level data on renewable portfolio standards obtained from the Database of State Incentives for Renewables & Efficiency (DSIRE) database (Prasad and Munch, 2012; Crago and Chernyakhovskiy, 2017; Li and Yi, 2014).

2.4 Results

2.4.1. Variation in Fossil Fuel Mix in Electricity Generation

I explore the mix of fossil fuels used in electricity generation using linear panel data models with state and time fixed effects. I focus on coal and natural gas because the use of petroleum oil in electricity generation is minor relative to coal and natural gas. Table 4 shows state and time fixed effects regression results for shares of coal and natural gas use in electricity generation relative to total fossil fuel use in terms of relative MMBTUs. Two models are used to examine the change in respective fuel shares over time. Both models include a binary Period variable (1 for 2009 and after, 0 otherwise)[20]. The results confirm a significant drop (increase) in the share of coal in model A (natural gas in model B) after 2009, consistent with retirements and conversions of coal plants with limited replacement as observed in EIA data. The EIA data show that at the end of 2011 about 1,308 coal-fired generating units with a capacity of 310 GW were operating in the United States. However, in 2012 alone, 10.2 GW of coal-fired capacity was retired, representing about 3.2% of the 2011 total. Table 4 results indicate significant negative (positive) own (cross) price effect of natural gas.

I also observe that the coefficient for electricity generation is negative and significant in model A. This implies that growth in electricity generation from fossil fuels (see also EIA, 2017) is associated with a significant drop in the share of coal relative to natural gas across states. The results in Table 4

Island (RI), North Carolina (NC), Utah (UT), California (CA) and Vermont (VT).

[20] I use Zivot-Andrews (Zivot and Andrews, 2002) endogenous structural break test and the Chow test (Chow, 1960) for individual data series to identify the break-date (the largest Chow statistic) among all possible break dates (Quandt, 1960; Hansen, 2001). Figures 2.A1 and 2.A2 (in the Appendix) indicate 2009 as the most prevalent break date across the series. Natural gas price series have a structural break in 2009 in more than 30 states.

suggest that on average, across states coal intensity of electricity generation has declined due to the increased availability of low-priced natural gas. In addition to the direct substitution effect the impact of lower natural gas prices maybe also manifested through its moderating impact on electricity prices thereby reducing the economic viability of coal-based generators.

Table 4: State and Time Fixed Effect Regression Results for Fossil Fuel Shares in Electricity Generation

	A. Share Coal	B. Share N. Gas
Log Electricity Generation	-0.141 (0.05)***	0.117 (0.06)*
Coal Price	0.004 (0.03)	0.024 (0.03)
NG Price	0.018 (0.01)**	-0.020 (0.01)**
Period2	-0.209 (0.06)***	0.220 (0.06)***
RPS	-0.015 (0.03)	0.033 (0.03)
R-Squared	0.348	0.372
Observations	Balanced panel n=43, T=17 and N=731	

*Standard errors in brackets; Significance levels: 1% '***' 5%'**' 10% '*'*

2.4.2. Fossil Fuel Substitution

Tables 5 and 6 show average substitution elasticities (σ_{CN}) and corresponding price elasticities (own: ε_{NN} and ε_{CC}, and cross: ε_{CN} and ε_{NC}) for 2001-2008 and 2009-2017. Individual state elasticities are obtained from electricity market specific regressions (system 2.3), as defined by FERC (2019), for each of the two periods using state level data. The following electric power regions are considered: MISO (Midcontinent), ISO-NE (New England), NYISO (New York), Northwest, PJM (Pennsylvania-New Jersey-Maryland Interconnection), Southeast, Southwest, SPP (Southwest Power Pool) and ERCOT (Texas). I formally test whether the respective mean elasticities across states in each region changed significantly between two periods using pairwise tests. The results are provided in the last columns of Tables 5 and 6. The null hypothesis is that there is no difference in mean elasticities across the two periods. The results show that substitutability between coal and natural gas increased post-2009 in MISO, Northwest, PJM, Southeast, SPP and NYISO. Three regions (ISO-NE, Southwest and ERCOT) show statistically insignificant changes. Hence, an increased supply of natural gas enabled greater substitution between coal and natural gas on average in most regions and in most states[21]. Significant changes coincide with increased capacity of gas-fired generation and retiring or retrofitting coal-fired plants to meet emission standards (see FERC, 2012; Gao et al., 2013).

Table 5: Fossil Fuel Substitution Elasticities

Electricity Regions	Pre-2009 Mean	Post-2009 Mean	Pairwise T-Test P-value
MISO	0.001(3.35)	0.92 (0.23)*	0.080*
ISO-NE	0.55 (0.91)	0.93 (1.02)	0.33
Northwest	-0.76 (2.55)	0.73 (0.62)	0.05**
PJM	-0.04 (0.48)	0.29 (0.28)	0.06*
Southeast	0.14 (0.29)	0.40 (0.31)	0.08*
Southwest	0.26 (0.48)	0.33 (0.08)	0.44
SPP	-0.22 (0.23)	0.72 (1.36)	0.05**
NYISO	-9.33 (0.05)***	1.22 (0.18)**	0.00***
ERCOT	2.85 (0.10)***	0.83 (1.69)	0.10

*Significance levels: 1% '***' 5%'**' 10% '*'*

Heterogeneity of elasticities across states (as indicated by high relative standard deviations) in each region, illustrates the complexity of the interdependencies that can be disguised by regional and national elasticity estimates. The elasticities of substitution vary even among the states within the electricity markets (see Table 2.A1 in the Appendix). For example, the elasticities of substitution between coal and natural gas are statistically significant in CT pre and post-2009 and insignificant in other states in the ISO-NE region. In the PJM region, only VA had a significant elasticity of substitution between coal and natural gas in the pre-2009 period. In the Southwestern region, only AZ has significant elasticities of substitution in both periods.

[21] Table 2.A1 (in the Appendix) provides estimated substitution elasticities for states with statistically significant estimates.

Table 6: Price Elasticities

Estimates	Pre 2009		Post 2009		Pairwise Test
	Mean	Std. Dev.	Mean	Std. Dev.	P-value
Own Price Elasticities					
$\varepsilon_{Coal\text{-}Coal}$	-0.228	0.235	-0.150	0.373	0.277
$\varepsilon_{N.Gas\text{-}N.Gas}$	-0.289	0.461	-0.385	0.276	0.198
Cross Price Elasticities					
$\varepsilon_{Coal\text{-}N.Gas}$	0.050	0.147	0.329	0.341	0.009***
$\varepsilon_{N.Gas\text{-}Coal}$	-0.117	1.164	0.283	0.198	0.014**

*Significance levels: 1% '***' 5% '**' 10% '*'*

On average own price elasticities for natural gas (coal) increased (decreased) across the two periods (Table 6). I estimated price elasticities at the state level and confirmed that own price elasticities for natural gas (ε_{NN}) and coal (ε_{CC}) have expected signs in both periods[22]. Own price elasticities are comparable to the estimates in prior literature. Ko and Dahl (2001) use monthly US 1993 data to obtain national coal own price elasticity of -0.6 and natural gas own price elasticity of -1.5. Gao et al., (2013) use data from seven US electricity market regions from 2001 to 2008 and report own price elasticities for coal demand ranging between -1.76 and -0.07, and for natural gas ranging between -0.75 to -0.19. I observe that changes in own price elasticities from before to after 2009 are heterogeneous across states even when states are located in the same electricity market (Table 2.A2 and 2.A3 in the Appendix). For example, in the PJM region, statistically significant coal own price elasticities are observed in WV and VA but not in MD, OH and NJ. On average the results in Table 6 indicate an increase in cross price elasticities in 2009-2017 relative to 2001-2008. The changes are again heterogeneous across regions and states (Tables 2.A4 and 2.A5 in Appendix).

[22] Tables 2.A2 to 2.A5 (in the Appendix) provide estimates of own price and cross price elasticities for states where estimates are statistically significant.

2.4.3. Stochastic Frontier Analysis

The results from the Stochastic Frontier regressions are provided in Table 7.[23] Probability density function (λ) and variances of the disturbances (σ_u and σ_v) from the TFE-MLE model suggest that the variability in the frontier estimation is also emanating from technical inefficiency. Breusch-Pagan and White statistic tests for heteroscedasticity of the inefficiency term across states fail to reject the constant variance assumption. In this respect, WMLE and MMSLE models are equally appropriate (Belotti and Ilardi, 2017). Translog cost function estimation in TFE-MLE and WMLE is based on state and time fixed effects. On the other hand, MMSLE failed to converge with time fixed effects in the pre-estimation as expected (Belotti and Ilardi, 2017). Therefore, in Table 7, I provide the results from only the TFE-MLE and WMLE models with state and time fixed effects in the cost function[24]. TFE-MLE results are preferred because they are based on a one-step estimation procedure (Wang and Schmidt, 2002). The results in Table 7 exclude time fixed effects in the second stage because I am interested in the average effect of the pre and post-2009 period on the inefficiencies[25].

The negative and significant coefficients for log of electricity generation (δ_2) in Model B indicate that efficiency is gained when more electricity is generated as one would expect based on economies of scale. This result is consistent with prior finding pertaining to the economies of scale in the US electricity generation (Kwoka, 2005; Knittel, 2002). Cost ratio of coal and natural gas has a significant effect on inefficiency based in the TFE-MLE. Cost ratio impacts depend on the combined effects of changes in fuel quantities and prices. Since natural gas is more efficient than coal (Knittel, 2002; Seifert et al., 2016; See and Coelli, 2012; EIA, 2012a), I expect inefficiency to drop with increase

[23] I only show results from the inefficiency model and skip coefficient estimates from the translog cost function because the interest at this point pertains to the determinants of inefficiency. Estimates from the translog SFA cost function are available upon request.

[24] The results from the MMSLE model without the time fixed effects are available upon request.

[25] The results from TFE-MLE and WMLE models with state and time fixed effects in both stages are available upon request. The conclusion from these results are similar to the results in Table 7 in terms of the effect of the elasticities of substitution and electricity generation on inefficiencies.

in the share of natural gas over coal. However, the cost ratio also depends on the relative prices of coal and natural gas. Increase in the relative price of coal leads to an increase in the use of natural gas. Hence, the combined effect of prices and quantities on the cost ratio is theoretically ambiguous.

Table 7: Stochastic Frontier Estimation Results (TFE –MLE; Green 2005)

	Variable description	A. TFE –MLE; (Green 2005)	B. WMLE; (Chen et al., 2014)
		Est (Std. Error)	Est (Std. Error)
LL	Log Likelihood	191.650	[a]
λ	Lambda	2.525 (0.01)***	[a]
σ_u	Sigma_u	0.298 (0.00)***	[a]
σ_v	Sigma_v	0.118 (0.01)***	[a]
	Inefficiency Parameters		
δ_1	Per-capita energy consumption	0.063 (0.04)	-0.034 (0.01)***
δ_2	Log of electricity generation	-0.041 (0.04)	-0.073 (0.04)**
δ_3	Cost ratio (Coal/NG)	-3.306 (0.43)***	$-0.1*10^{-3}$ (0.0)
δ_4	Renewable Portfolio Standards	-0.637 (0.26)**	0.019 (0.03)
δ_5	Net addition of generation capacity	$-0.1*10^{-4}$(0.00)	$-0.1*10^{-4}$(0.0)*
δ_6	Elasticity of substitution, $\sigma_{C\text{-}NG}$	-0.146 (0.05)***	-0.001 (0.00)*
δ_7	Time	0.062 (0.04)	0.004 (0.00)
δ_8	Period2	-0.106 (0.39)	-0.024 (0.03)
	Panel data	T=17, n=43; N=731	

*Standard errors in brackets; parameters not reported[a]; Significance levels: 1% '***' 5%'**' 10% '*'*

Statistically significant coefficients of the elasticity of substitution (δ_6) indicate that an increase in the elasticity of substitution between coal and natural gas improves technical efficiency. These results provide evidence of the positive relationship between the elasticity of substitution and technical efficiency. Previous studies have discussed the relevance of the elasticity of substitution for economic growth, technical change, and productivity (Hicks, 1932; de La Grandville, 1989; Klump and de La Grandville 2000). However, the role of elasticity of substitution for energy production efficiency has not been addressed. the results show a negative effect of the elasticity of substitution between coal and natural gas on technical inefficiency in fossil fuel based electricity generation.

The results (Model A) also show that renewable portfolio standards (RPS) have a positive effect on technical efficiency. If natural gas based generation complements adoption of renewables, then greater adoption of renewables and greater natural gas based generation may be expected to improve technical efficiency of fossil fuel based generation. Greater use of natural gas relative to coal would be expected to yield gains in technical efficiency of fossil fuels-based electricity generation (Knittel, 2002; Seifert et al., 2016; See and Coelli, 2012). On the other hand, if growth in renewable energy is not necessarily accompanied with an increase in natural gas based generation, then the effect of RPS and the associated increase in renewable generation on technical efficiency is theoretically ambiguous.

Previous literature has documented a positive association between time and energy generation inefficiency using both aggregate (Fatima and Barik, 2012) and plant level data (See and Coelli, 2012; Seifert, Cullman and von Hirschhausen, 2016; Hattori, 2002; Khanna et al., 1999). Increase in inefficiency over time is generally attributed to deteriorating equipment. However, retirements of older power plants and installation of newer power plants are expected to improve technical efficiency. the results show that time (δ_7) and period dummy (δ_8) are statistically not significant. The data show that during 2001-2017 about 6.1GW were retired on average per year across all states, which is less than 2.3% of total generation. 16.3GW on average was added each year. The decrease in inefficiency (though not statistically significant) in the 2009-2017 period is consistent with the overall increase in natural gas based electricity generation relative to coal based generation. Natural gas-based generation, which is more efficient than coal-based generation (Knittel 2002, EIA 2012a) has been steadily increasing EIA (2012b).

I also observe that inefficiency decreased in most states but increased in some states across the two periods. Overall, estimated inefficiency scores range from 0.09 to 0.46 with mean 0.19 and are comparable to estimates in previous literature. Chen et al., (2014) used a panel of US steam electric power generation data to estimate stochastic frontier production function. They found mean technical inefficiencies of 0.111 and 0.107 using WMLE and TFE-MLE, respectively. Rungsuriyawiboon and

Stefanou, (2007) used US utilities data from 1986 to 1999 for steam electric power generation and found inefficiency scores in the range of 0.212 to 0.265. Knittel, (2002) found mean technical inefficiency of 0.1757 using data from a large set of coal and natural gas generation units from 1981 to 1996.

2.4.4. Fossil Fuel Substitution and CO_2 Emissions

Technical efficiency in electricity generation has implications for CO_2 emissions (Lee, & Zhang., (2012); Guo, Zhu, Fan, & Xie., (2011); Zhou, Ang, & Poh., (2008)). Having observed a negative relationship between technical inefficiency and elasticity of substitution I examine the relationship between inter-fuel substitution and carbon dioxide emissions using state and time fixed effects regression. Electricity producers minimize costs (equation (2.1)), in response to fuel prices with corresponding implications for technical efficiency and CO_2 emissions. As a result, fossil fuel substitution induced by relative price changes of coal and natural gas can affect carbon emission. The standard panel regression model (equation (2.7)), with state and time fixed effects, is used to test whether CO_2 emissions respond to changes in elasticity of substitution between coal and natural gas. Results from the regression are reported in Table 8.

The results in Table 8 show that the elasticity of substitution between coal and natural gas has a significant and negative association with CO_2 emissions. This result is consistent with Suh (2019) in terms of confirming the significance of interfuel substitution for CO_2 emissions. An increase in the state level elasticity of substitution between coal and natural gas leads to a decrease in CO_2 emissions. In this respect, natural gas can be viewed as an important resource for reducing the carbon footprint of electricity generation relative to more coal-intensive generation when additional natural gas based generation increases substitution elasticity (see Sims, Rogner and Gregory, 2003). the results also indicate that with increased availability of natural gas post-2009, CO_2 emissions decreased. These results are important for formulating or implementing energy and environmental policies because inter-fuel substitution has implications for CO_2 emissions.

Table 8: State and Time Fixed Effects Regression Results for CO_2 Emissions

Dep-log CO_2 Emissions	Coef (Std. Error)
Electricity production	0.512 (0.09)***
Elasticity of substitution	-0.005 (0.00)*
RPS	-0.019 (0.03)
Period2	-0.224 (0.03)***
Constant	11.96 (0.99)***
R-sq	0.75
Observations	n=43, T=17 and N=731

*Standard errors in brackets; Significance levels: 1% '***' 5%'**' 10% '*'*

2.5 Conclusion

Heterogeneity of elasticities across major electricity production regions in the US has been documented in previous literature (Gao et al., 2013). This study shows that the differences in terms of elasticities of substitution, as well as technical inefficiencies, can be observed not only across major electricity regions but also across the states within those regions. The elasticities of substitution differ even across states that are located within the ten major electricity regions, as defined by the Federal Energy Regulatory Commission (Gao et al., 2013). Furthermore, I observe significant heterogeneity of technical inefficiency across states. Such heterogeneity may be present due to differences in resource endowments, technologies, institutional backgrounds, or state policies. The results show that elasticities of substitution have a statistically significant relation with technical efficiency and carbon emissions in electricity generation. I find that an increase in the elasticity of substitution between natural gas and coal has a positive relation with technical efficiency and a negative effect on CO_2 emissions. I also observe that state level elasticities of substitution and technical inefficiencies pre- and post- 2009 changed differently across states.

The results imply that changes in generation technology mix can influence technical efficiency in part through associated changes in coal and natural gas substitution elasticity. These findings suggest the need for careful analysis and planning for anticipated retirements of power generation units at regional scales. Over the past ten years most of the retired power plants have been fossil fuel based. Upcoming retirements through 2020 are also expected to be mostly coal plants and gas steam turbines (EIA, 2018). These changes will likely have spatially heterogeneous implications for natural gas and coal elasticities of substitution, technical efficiency of generation, and CO_2 emissions. With greater elasticity of substitution, a decline in CO_2 emissions can be expected. On the other hand, policies or changes in technology mix that may decrease elasticity of substitution can lead to increase in CO_2 emissions. Therefore, policies that may negatively affect elasticities of coal and natural gas substitution should consider associated increase in CO_2 emissions. Policy implications for elasticity of substitution should also be considered at spatial disaggregated scales as the results document heterogeneous changes in elasticities of substitution in response to greater availability of natural gas.

Electricity generation sector has adapted to the increased availability of economically recoverable natural gas reserves, and in April of 2015 for the first time, natural gas based electricity generation in the US surpassed coal powered electricity generation on a monthly basis (EIA, 2016). EIA forecasts also indicate that the share of gas-fired electricity generation will continue to rise but will fluctuate depending on relative fuel prices and infrastructure investments. State level fossil fuel substitution capabilities in electricity generation are limited due to technologic parameters of power plants, investment in new gas-fired power plants, and natural gas storage and shipping infrastructure. Although planned and existing pipeline infrastructure has been found to be adequate for anticipated needs of electric power sector (DOE, 2015), natural gas storage capacity can still limit the use of natural gas in electricity generation in some regions. Nevertheless, heterogeneity in fuel substitution across states, as documented in this study, highlights the need for understanding the implications of growing natural gas-based electricity generation and declining coal based generation for regional electric system operations including technical efficiency and CO_2 emissions. It is important for policy makers and the industry to understand the evolving fuel-substitution capabilities at the state levels to account for the electric power industry's ability to respond to changes in the regulatory environment and relative fuel prices by adjusting fuel mix in electricity generation within and across utilities and states.

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APPENDIX

Table 2.A1. Elasticities of Substitution for Coal-Natural Gas (σ_{CN})

		2001-2008		2009-2017		Elasticity Change	
Region	State	σ_{1CN}	s.e(σ_{1CN})	σ_{2CN}	s.e(σ_{2CN})	σ_{2CN}-σ_{1CN}	s.e(σ_{2CN}-σ_{1CN})
MISO	AR	1.59	(0.31)***	0.71	(0.43)	-0.88	(0.53)
MISO	IA	1.46	(0.63)*	0.51	(1.63)	-0.95	(1.75)
ISO-NE	CT	1.36	(0.54)**	1.65	(0.46)***	0.29	(0.71)
ISO-NE	MA	-0.03	(0.79)	1.8	(0.32)***	1.84	(0.85)*
NYISO	NY	-9.33	(0.71)***	1.22	(0.42)**	10.56	(0.83)***
NorthWest	NV	-1.34	(0.48)**	1.41	(0.68)*	2.76	(0.83)**
PJM	VA	-1.51	(0.62)**	-0.56	(1.41)	0.95	(1.54)
SouthEast	AL	0.59	(0.10)***	0.69	(0.66)	0.10	(0.67)
SouthEast	GA	0.58	(0.23)**	0.90	(1.23)	0.31	(1.25)
SouthWest	AZ	-0.43	(0.14)**	0.49	(0.11)***	0.92	(0.18)***
SouthWest	NM	0.95	(0.30)**	0.50	(0.24)*	-0.46	(0.39)
ERCOT	TX	2.85	(0.31)***	0.83	(1.460	-2.02	(1.50)

*Standard errors in brackets; Significance levels: 1% '***' 5% '**' 10% '*'*

Table 2.A2. Own Price Elasticities for Coal (ε_{CC})

		2001-2008		2009-2017		Elasticity Change	
Region	State	ε_{1CC}	s.e(ε_{1CC})	ε_{2CC}	s.e(ε_{2CC})	ε_{2CC}-ε_{1CC}	s.e(ε_{2CC}-ε_{1CC})
MISO	AR	-0.50	(0.12)***	-0.41	(0.24)	0.09	(0.27)
MISO	MS	-0.83	(0.24)**	-0.78	(0.47)	0.05	(0.53)
MISO	ND	-0.25	(0.18)	0.88	(0.50)	1.13	(0.53)**
ISO-NE	MA	-0.37	(0.66)	-0.58	(0.23)**	-0.21	(0.70)
NYISO	NY	-0.48	(0.13)***	-0.20	(0.28)	0.28	(0.31)
NorthWest	NV	0.02	(0.25)	-1.90	(0.55)**	-1.92	(0.60)**
NorthWest	WA	0.15	(0.14)	-0.59	(0.30)*	-0.74	(0.33)**
PJM	VA	-0.84	(0.25)**	-0.61	(0.42)	0.23	(0.49)
PJM	WV	-0.43	(0.18)**	0.12	(0.24)	0.55	(0.30)
SouthEast	AL	-0.19	(0.05)***	-0.35	(0.39)	-0.16	(0.39)
SouthWest	AZ	-0.19	(0.14)	-0.55	(0.05)***	-0.36	(0.15)**
SouthWest	CO	0.01	(0.14)	-0.17	(0.08)*	-0.18	(0.16)
SouthWest	NM	-0.62	(0.42)	-0.33	(0.15)*	0.29	(0.45)
SPP	SD	-0.75	(0.21)***	0.21	(1.17)	0.96	(1.19)
ERCOT	TX	-0.13	(0.02)***	-0.31	(0.28)	-0.18	(0.28)

*Standard errors in brackets; Significance levels: 1% '***' 5% '**' 10% '*'*

Table 2.A3. Own Price Elasticities for Natural-Gas (ε_{NN})

		2001-2008		2009-2017		Elasticity Change	
Region	State	ε_{1NN}	s.e(ε_{1NN})	ε_{2NN}	s.e(ε_{2NN})	ε_{2NN} - ε_{1NN}	s.e(ε_{2NN} - ε_{1NN})
MISO	AR	-1.15	(0.19)***	-0.43	(0.25)	0.73	(0.31)*
ISO-NE	CT	-0.51	(0.15)**	-0.29	(0.04)***	0.22	(0.16)
ISO-NE	MA	-0.29	(0.30)	-0.60	(0.09)***	-0.32	(0.32)
ISO-NE	ME	-0.26	(0.23)	-0.51	(0.08)***	-0.25	(0.24)
NYISO	NY	-2.85	(0.42)***	-0.69	(0.12)***	2.15	(0.44)***
NorthWest	NV	-0.14	(0.31)	-0.73	(0.17)***	-0.59	(0.35)
PJM	DE	-0.49	(0.16)**	-0.11	(0.28)	0.38	(0.33)
SouthEast	AL	-0.38	(0.06)***	-0.35	(0.33)	0.04	(0.33)
SouthEast	FL	-0.43	(0.11)***	-0.11	(0.47)	0.33	(0.48)
SouthEast	GA	-0.48	(0.18)**	-0.54	(0.73)	-0.06	(0.75)
SouthWest	AZ	-0.10	(0.03)**	-0.25	(0.05)***	-0.15	(0.06)**
SouthWest	CO	-0.13	(0.06)*	-0.02	(0.14)	0.11	(0.15)
SouthWest	NM	-0.18	(0.04)***	-0.16	(0.08)*	0.02	(0.09)
ERCOT	TX	-2.28	(0.16)***	-0.73	(1.10)	1.55	(1.11)

*Standard errors in brackets; Significance levels: 1% '***' 5% '**' 10% '*'*

Table 2.A4. Cross Price Elasticities for Coal-Natural Gas (ε_{CN})

		2001-2008		2009-2017		Elasticity Change	
Region	State	ε_{1CN}	s.e(ε_{1CN})	ε_{2CN}	s.e(ε_{2CN})	ε_{2CN}- ε_{1CN}	s.e(ε_{2CN}- ε_{1CN})
MISO	AR	0.70	(0.14)***	0.30	(0.18)	-0.40	(0.23)
MISO	IA	0.37	(0.16)**	0.09	(0.29)	-0.28	(0.33)
ISO-NE	CT	0.85	(0.34)**	1.43	(0.40)***	0.58	(0.53)
ISO-NE	MA	-0.02	(0.42)	1.32	(0.23)***	1.33	(0.48)**
NYISO	NY	-1.31	(0.10)***	0.81	(0.28)**	2.12	(0.30)***
NorthWest	NV	-0.57	(0.20)**	0.89	(0.43)*	1.46	(0.47)**
PJM	VA	-0.46	(0.19)**	-0.21	(0.53)	0.25	(0.56)
SouthEast	AL	0.21	(0.04)***	0.35	(0.33)	0.14	(0.34)
SouthEast	GA	0.12	(0.05)**	0.37	(0.51)	0.26	(0.52)
SouthWest	AZ	-0.29	(0.09)**	0.26	(0.06)***	0.55	(0.11)***
SouthWest	NM	0.75	(0.24)**	0.34	(0.16)*	-0.42	(0.29)
ERCOT	TX	0.18	(0.02)***	0.15	(0.27)	-0.03	(0.27)

*Standard errors in brackets; Significance levels: 1% '***' 5% '**' 10% '*'*

Table 2.A5. Cross Price Elasticities for Natural Gas-Coal (ε_{NC})

		2001-2008		2009-2017		Elasticity Change	
Region	State	ε_{1NC}	s.e(ε_{1NC})	ε_{2NC}	s.e(ε_{2NC})	ε_{2NC}- ε_{1NC}	s.e(ε_{2NC}- ε_{1NC})
MISO	AR	0.84	(0.16)***	0.41	(0.25)	-0.43	(0.30)
MISO	IA	1.05	(0.45)*	0.41	(1.30)	-0.64	(1.38)
ISO-NE	CT	0.22	(0.09)**	0.11	(0.03)***	-0.12	(0.09)
ISO-NE	MA	-0.01	(0.17)	0.35	(0.06)***	0.36	(0.18)*
NYISO	NY	-2.93	(0.22)***	0.22	(0.08)**	3.15	(0.24)***
North-West	NV	-0.73	(0.26)**	0.51	(0.24)*	1.24	(0.36)**
PJM	VA	-0.82	(0.34)**	-0.30	(0.75)	0.53	(0.82)
South-East	AL	0.37	(0.06)***	0.34	(0.32)	-0.04	(0.33)
South-East	GA	0.46	(0.18)**	0.52	(0.71)	0.06	(0.73)
South-West	AZ	-0.14	(0.05)**	0.22	(0.05)***	0.36	(0.07)***
South-West	NM	0.20	(0.06)**	0.16	(0.08)*	-0.04	(0.10)
ERCOT	TX	2.59	(0.28)***	0.68	(1.18)	-1.92	(1.22)

*Standard errors in brackets; Significance levels: 1% '***' 5% '**' 10% '*'*

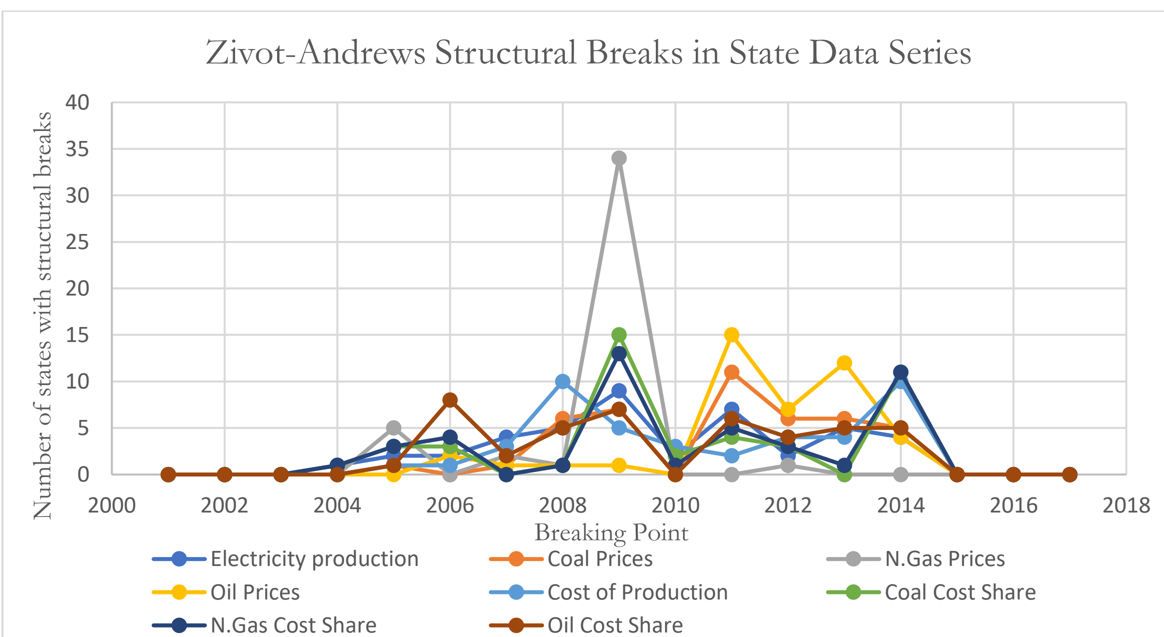

Figure 2.A1. Distributions of Zivot-Andrews structural breaks

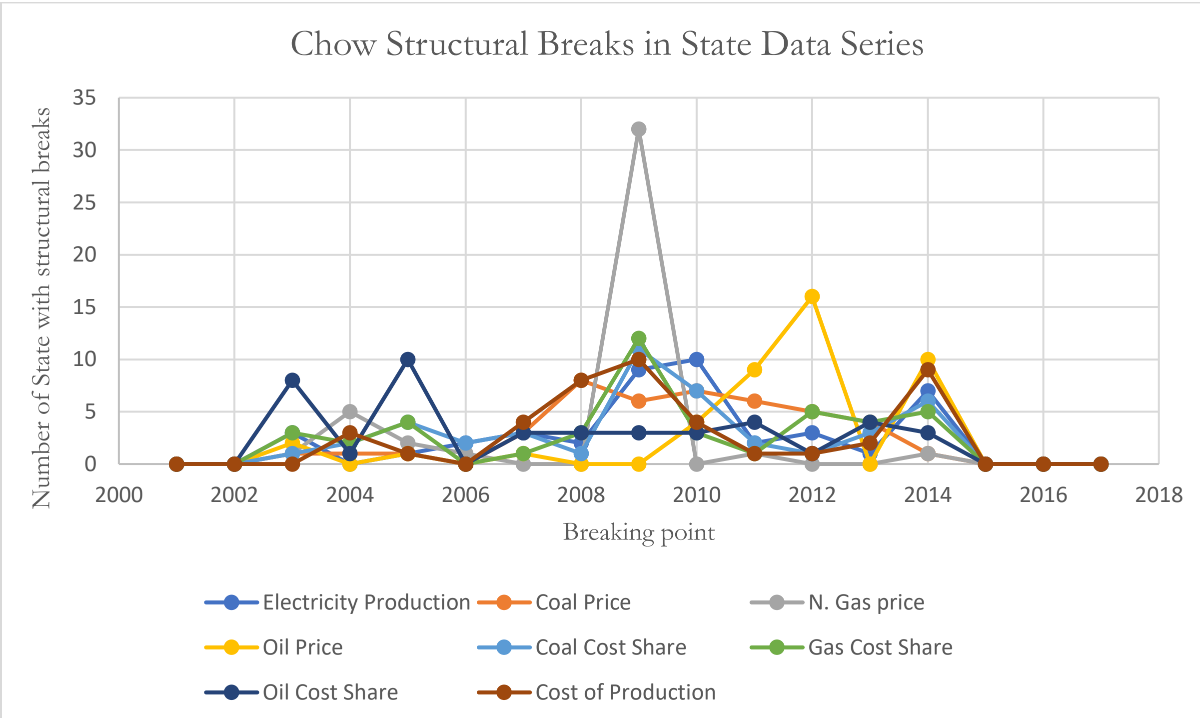

Figure 2.A2. Distributions of Chow structural breaks

CHAPTER 3. All the DUCs in a Row: Natural Gas Production in the US.

Abstract

Using data from seven shale gas regions in the United States, I examine natural gas production in terms of drilling rig activity and well completion rates. the objectives are to examine the role and determinants of well completion decisions in the US natural gas production. I observe that in recent years, the explanatory power of drilling rig count has declined. On the other hand, the number of producing wells remain a significant factor in explaining the variation in gas production. I find that an increase in the number of drilled but uncompleted wells (DUCs) has a significant role in natural gas supply. The number of DUCs depends on drilling rig activity and futures prices of oil and natural gas. Also, the results indicate that well completion decisions and the duration of DUC status depend on oil and gas prices, pipeline capacity, producing well type and well depth.

Keywords: Natural Gas Production, Rig Count, Well Completion, Drilled and Uncompleted Wells.

JEL CLASSIFICATION: L71, Q30, Q41, D22

3.1 Introduction

Understanding the determinants of natural gas supply is important because of its significance for the US power sector (Peters and Hertel, 2017; Stephens, 2018) and US economic activity in general (Arora and Lieskovsky, 2014; Melick, 2014; Weber, 2012; Joskow, 2013)[26]. Previous academic literature relied on drilling rig activity (measured in terms of the count of actively drilling rigs) as the primary determinant of oil and gas production because of the simplicity, availability, and global applicability of drilling rig count as an indicator (Apergis, Ewing and Payne, 2016; Melek, 2015). The oil and gas industry also has been relying on rig count as a measure of oil and gas production activity[27]. However, as Figure 7 illustrates, natural gas production in the US increased even though drilling activity, measured in terms of the number of actively drilling rigs, has declined in recent years (EIA, 2019a).

Along with the growth in the use of hydraulic fracturing and horizontal drilling technologies, market analysts, researchers and government agencies have noted the increase in the inventory of drilled but uncompleted wells (DUCs) in the US (Hegarty, 2017; EIA 2013; EIA 2019b; Dunning, 2016; Srinivasan, Krishnamurthy and Kaufman, 2019; IHS, 2016; Piotrowski, 2016). However, little or no systematic information is available on the growth of DUC inventory and the implications for natural gas production. This paper examines the determinants of DUC inventories and the impacts of drilling rig activity and well completion on natural gas output in the US.

Technological developments in unconventional oil and gas (UOG) production have transformed the US gas industry. According to the US EIA, domestic production of gas from the UOG industry grew by more than 100 % from 2000 to 2010. Data from the EIA (2016a) also indicate that daily production of US dry shale increased from 2.5 in 2002 to 43 billion cubic feet in 2016, with

[26]Large number of studies also document the relationship between energy in general and economic growth (See Hamilton, 2013).
[27]For example, Baker Hughes has been reporting rig count since 1944 (Baker Hughes, 2019).

most of the new production coming from the Northern Appalachian basin (Marcellus and Utica shale units). Substantial gains in productivity continue through advances such as super pads (which can include up to 20 wells), extended horizontal laterals (reaching up to 20 thousand feet[28]) and improved drilling and fracturing technologies. The share of horizontally drilled wells increased from 3% in 2008 to 12% in 2017 (EIA 2018). As a result, although the number of drilling rigs fell since 2014, natural gas production has continued to grow (Figure 7) (EIA, 2019a).

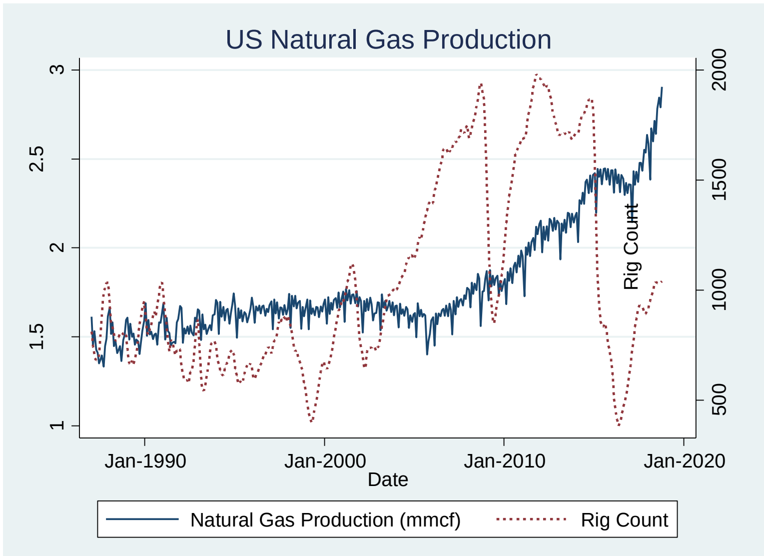

Figure 7: US rig activity and natural gas production

In general, UOG production involves two stages. The first stage involves drilling, casing the well with multiple strings of steel pipe, and cementing the pipe. In the second stage (completion), the steel casing is perforated, and the well is stimulated via hydraulic fracturing to initiate gas flow from fractured formations. Completion, which can be significantly more expensive and time consuming than the first stage activities, can be delayed indefinitely. However, interrupting the flow from a producing well can be prohibitively costly in terms of foregone income (Kleinberg et al., 2018). Hence, production timing decisions take the form of drilling and completion decisions corresponding to

[28]See Eclipse Purple Hayes well at 20,803 feet.
https://www.hartenergy.com/exclusives/super-laterals-going-really-really-long-appalachia-31209

stages one and two, respectively (Mason and Roberts, 2018). Wells drilled (stage one), but not hydraulically fractured or completed are labeled as drilled but uncompleted wells (DUCs).

Figure 8 shows that the aggregate number of DUCs has increased since 2007 across all regions. From November 2016 to the end of 2017, the number of DUCs rose 37.4% to 7,493 (DI, 2016). EIA's (2019a) drilling productivity report shows more than 8,700 DUCs as of November 2018. Growth in DUCs varies by region, with the largest increase observed in the Permian Basin. The reasons for the delays in well completion, and consequent growth in the DUC numbers, may include: shortage of hydraulic fracturing equipment and teams, contractual lease obligations that require active well development in stage one, pipeline capacity bottlenecks, and operators' timing decisions to take advantage of favorable prices (EIA, 2019b; Kleinberg et al., 2018).

One implication of the increase in DUCs is that aggregate natural gas production depends less on drilling rig activity and more on well completion rates. As a result of growth in unconventional production, and associated two-stage production technology use, drilling rig counts no longer directly correspond to the number of producing wells. Hence, the number of completed wells may be increasingly important for modeling natural gas production. Though the drilling rig count remains an important factor in natural gas production, increase in production is achieved with fewer drilling rigs given improvements in drilling technology and the backlog of DUCs (EIA, 2019a)

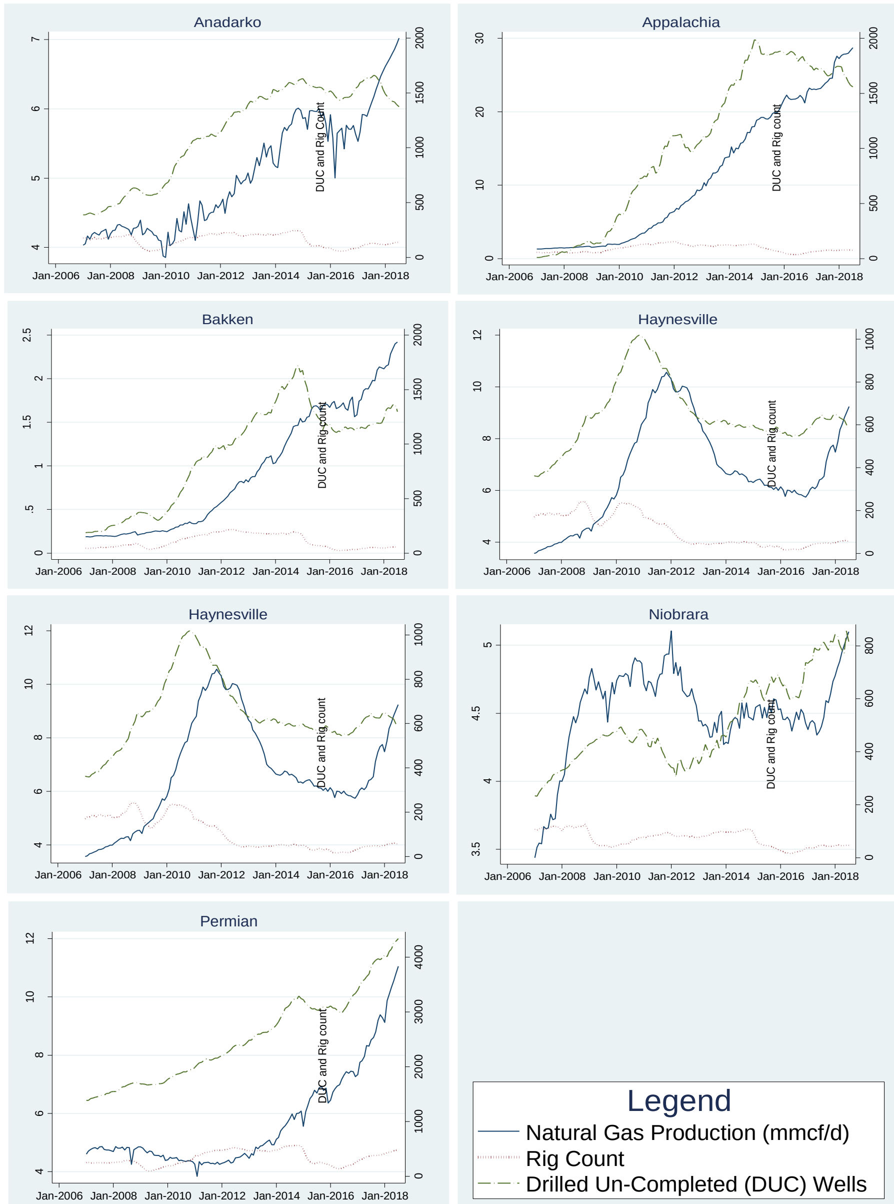

Figure 8. Rig count, drilled and un-completed well count, and natural gas production trends from 2007-2018

Importantly, for overall production to grow, the productivity of new wells must offset declines in productivity of legacy wells (Boyce and Nøstbakken, 2011). Therefore, this paper considers both the number of producing wells and the number of newly completed wells as drivers of natural gas output. The objectives of this study are threefold. First, I examine the role of well completion rates in explaining natural gas production. Second, I examine the determinants of DUC numbers, which represent the gap between drilled and completed wells. Third, I identify the factors that influence the length of time that operators take to complete unconventional wells.

The literature on the determinants of natural gas production is limited. Iledare (1995) uses a supply model for natural gas reserve additions in West Virginia to study the responsiveness of drilling effort and gross reserve additions to changes in the expected wellhead price, taxes, resource depletion and reserve life index. He concludes that drilling activity shifts across geological formations in response to varying geologic conditions and economic incentives. Boyce and Nøstbakken (2011) show a positive correlation between output prices and drilled wells, enabled by a significant decrease in the cost of drilling. Chen and Linn (2017) examine the effects of oil and gas futures prices on drilling activity in the US and the rest of the world. They show that drilling activities respond to futures prices more than spot prices. This is consistent with the industry practice of hedging gas production. Gülen et al., (2013) also document the sensitivity of drilling new wells to changes in natural gas prices. Similar results with a positive association between oil rig activity and crude oil prices have been documented by Ringlund, Rosendahl and Skjerpen (2008), Apergis et al. (2016), Anderson, Kellogg, and Salant (2018) and Khalifa, Caporin and Hammoudeh (2017).

Mason and Roberts (2018) examine the sensitivity of well level natural gas production in Wyoming to geologic and economic factors. They show that geologic factors affect intra-well production variation (well productivity) while prices affect inter-well production changes (number of producing wells) via producer drilling decisions. They conclude that after a well has started producing, prices have limited effect on well-level production. Instead, geologic and engineering factors determine well productivity. However, prices have a significant effect on total supply due to the elasticity of producers' drilling decisions. The authors show that at lower prices, only the most productive wells are drilled, while higher prices enable drilling of less productive wells. They also observe that the elasticity of drilling decisions in Wyoming increased since the use of horizontal drilling and hydraulic fracturing technologies. Ikonnikova and Gulen (2015) also examine the effect of prices on drilling activities in Barnett, Haynesville, and Fayetteville shale units. They show that at lower prices, producers in some locations may find it more profitable to rely on low-cost infill[29] wells to minimize capital costs as opposed to drilling relatively more productive but costlier wells in new locations.

None of the previous studies examine growth in DUC numbers and the relationships between gas production, drilling rig activity and well completion across shale regions in the US. I disentangle these variables, which allows us to present a more nuanced account of production activities given the recent growth in the number of drilled but uncompleted wells. the results document greater explanatory power of the number of producing wells relative to the count of active rigs for modeling natural gas production[30]. I also show that changes in oil and gas futures prices and drilling rig activity affect DUC numbers and the length of time that operators take to complete individual drilled wells.

3.2 Data

Unconventional shale gas production makes up more than 50% of all-natural gas produced in the US and its contribution continues to increase with most of the production coming from seven major shale regions (EIA, 2017). This study is based on the data from Anadarko, Appalachia (Marcellus and Utica), Bakken, Eagle Ford, Haynesville, Niobrara and Permian regions.

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[29]Infill wells are drilled and completed next to existing wells as opposed to new locations. Infill wells are less productive but require lower upfront capital costs by taking advantage of existing infrastructure and existing lease arrangements.
[30]Although the principles addressed in this study are applicable to both oil and gas production, I focus the analysis on unconventional gas production and reserve the analysis of oil production to future studies. I acknowledge that in some cases oil and gas production is joint. For example, unconventional production in the Permian basin is primarily aimed at oil with associated gas production.

I use monthly regional data from January 2007 to July 2018 to examine cumulative natural gas production and DUC counts, and daily well level data from 2000 to 2018 to estimate hazard ratios[31]. The data summary is presented in Table 9. Rig count and natural gas production[32] (million cubic feet - mmcf) data are obtained from the EIA. Well completion data obtained from DrillingInfo (now Enverus) include a monthly cumulative number of producing wells. Rig count data (disregarding the differences in rig requirements across regions due to geological characteristics) are provided by Baker Hughes.

Rig activity in this study reflects only the number of actively[33] drilling rigs. Figure 8 presents data trends for drilling rig counts, DUCs, and gas production. Since 2007, natural gas production has been increasing significantly in most regions, except in Niobrara and Haynesville. Substantial increase in production can be attributed to significant gains in productivity enabled by recent technological improvements. Haynesville lies deeper than the shale reservoirs in other regions making supply sensitive to price variation. Drilling rig activity in this region went down significantly and in 2016 drilling rig count dropped to 20 rigs.

To examine the growth in the number of DUCs, I use estimated monthly count of DUCs from January 2007 to July 2018[34]. Figure 8 shows that the numbers of DUCs have been increasing

[31]Natural gas production and DUC count analysis covers 2007 to 2018 because EIA data on monthly rig count and production per region are available only starting from January 2007. I used an expanded sample time frame in the survival analysis from January 2000 to July 2018 based on DUC duration data availability.
[32]EIA estimates natural gas production using data reported by various industry sources. In this study, I use up to date natural gas production numbers as reported by the EIA.
[33]The rig is active if it is drilling at least 15 days during the month. This measure excludes rigs involved in non-drilling activities like workovers and production testing. This definition is consistent with EIA (2019a) and Baker Hughes (2019).
[34]Estimates of DUC numbers can vary depending on methodologies, assumptions, and availability of data. EIA counts a drilled well to be uncompleted after 20 days' post spudding (EIA, 2016b). EIA started providing DUC count as of December 2013. To increase the sample size, I estimate DUCs using DrillingInfo well level data from January 2000 to July 2018 following the EIA methodology. Comparison of EIA DUC data and the estimated DUC numbers after 2013 reveals insignificant mean difference at 5% significance level in most regions except Appalachia and Permian. In these regions, the difference is insignificant at 1% level. The comparisons are available upon request. The minor difference in some regions can be due to the estimation method. the computations account for DUCs drilled since 2000. On the other hand, EIA excludes wells drilled prior to December 2013.

since 2007, with greater increases observed in Permian, Niobrara, and Anadarko regions. However, in Appalachia and Eagle Ford regions, the numbers of DUCs have decreased since 2014. The declines in the numbers of DUCs in Appalachia and Eagle Ford imply that completion of previously drilled but uncompleted wells has been outpacing drilling of new wells.

Table 9: Descriptive Statistics

Region	Variable	N.	Mean	Std. Dev.	Min.	Max.
All Regions	N.Gas Future Price ($/mcf)**	6,787	4.91	2.29	1.35	14.74
	Oil Future Price ($/b)**	6,787	62.41	27.20	14.06	145.90
Anadarko	Pipeline Capacity (10^3 mmcfd)**	139	16.3	2.7	13.3	19.3
	N.Gas Production (10^3 mmcf)/month*	139	5.1	0.8	3.9	7.0
	Rig Count/month*	139	155	55	55	247
	DUC Well Count 10^3/month*	139	1.1	0.4	0.4	1.7
	Producing Well Count 10^3/month*	139	16.2	2.7	9.8	19.7
	DUC Duration[35] (Days)**	14,840	88	121	1	1,778
	UOG Well Measured Depth[36] (10^3Ft)**	14,781	13.4	3.8	0.1	38.9
Appalachia	Pipeline Capacity (10^3 mmcfd)**	139	40.1	11.1	29.7	59.8
	N.Gas Production (10^3 mmcf)/month*	139	11.2	9.1	1.3	28.7
	Rig Count/month*	139	90	33	36	154
	DUC Well Count 10^3/month*	139	1.1	0.7	0.01	2.0
	Producing Well Count 10^3/month*	139	47.6	7.2	20.5	54.9
	DUC Duration (Days)**	14,649	317	249	1	1821
	UOG Well Measured Depth (10^3Ft)**	14,529	12.6	3.8	0.04	40.0
Bakken	Pipeline Capacity (10^3 mmcfd)**	139	7.7	0.4	7.2	8.1
	N.Gas Production (10^3 mmcf)/month*	139	0.9	0.7	0.2	2.4
	Rig Count/month*	139	105	64	24	218
	DUC Well Count 10^3/month*	139	0.9	0.5	0.2	1.7
	Producing Well Count 10^3/month*	139	6.2	4.7	0.5	13.2
	DUC Duration (Days)**	15,738	142	153	1	1656
	UOG Well Measured Depth (10^3Ft)**	15,705	18.8	3.4	1.9	27.2

[35] DUC duration variable measures length of time in days from end of drilling (spud date plus 20 days) to well completion or to first production for only completed unconventional wells. Minimum DUC duration of 1 day indicates that every region has at least 1 well which was completed in 21 days after spudding. Maximum DUC duration reflects maximum duration before the DUC well is treated as "dead". For the purpose of this study, outlier wells (wells drilled and not completed within the period of 5 years) are treated as "dead" DUCs and they constitute about 0.3% of the data.

[36] Well measured depth is the borehole and horizontal length of unconventional wells (horizontal and directional).

Eagle Ford	Pipeline Capacity (10^3 mmcfd)**	139	5.5	1.5	3.7	7.8
	N.Gas Production (10^3 mmcf)/month*	139	4.2	2.2	1.5	7.4
	Rig Count/month*	139	134	87	30	279
	DUC Well Count 10^3/month*	139	1.3	0.6	0.3	2.4
	Producing Well Count 10^3/month*	139	7.4	2.9	3.0	11.6
	DUC Duration (Days)**	25,230	149	204	1	1,821
	UOG Well Measured Depth (10^3Ft)**	25,225	14.9	3.2	0.4	39.4
Haynesville	Pipeline Capacity (10^3 mmcfd)**	139	38.4	6.0	30.4	46.8
	N.Gas Production (10^3 mmcf)/month*	139	6.7	1.9	3.6	10.6
	Rig Count/month*	139	104	73	16	244
	DUC Well Count 10^3/month*	139	0.6	0.2	0.4	1.0
	Producing Well Count 10^3/month*	139	15.7	3.0	8.1	18.7
	DUC Duration (Days)**	7,965	116	137	1	1,728
	UOG Well Measured Depth (10^3Ft)**	7,949	14.9	3.6	1.1	39.9
Niobrara	Pipeline Capacity (10^3 mmcfd)**	139	21.2	6.4	10.6	27.3
	N.Gas Production (10^3 mmcf)/month*	139	4.5	0.3	3.4	5.1
	Rig Count/month*	139	72	30	16	127
	DUC Well Count 10^3/month*	139	0.5	0.2	0.2	0.9
	Producing Well Count 10^3/month*	139	2.5	0.7	1.2	3.3
	DUC Duration (Days)**	11,872	133	150	1	1,821
	UOG Well Measured Depth (10^3Ft)**	11,373	11.5	3.6	0.4	40.0
Permian	Pipeline Capacity (10^3 mmcfd)**	139	16.6	2.5	13.3	20.2
	N.Gas Production (10^3 mmcf)/month*	139	5.7	1.7	3.8	1.0
	Rig Count/month*	139	335	132	92	565
	DUC Well Count 10^3/month*	139	2.5	0.8	0.4	4.3
	Producing Well Count 10^3/month*	139	109.3	21.8	30.4	136.9
	DUC Duration (Days)**	36,513	132	182	1	1,822
	UOG Well Measured Depth (10^3Ft)**	36,486	13.1	4.1	0.4	40.0

Continued…

*Note: **Data is from 2000- 2018 and *data is from 2007-2018.*

To explain the variation across regions and over time, I control for pipeline capacity, drilling rig count, and futures prices of natural gas (measured in dollars per thousand cubic feet) and oil (measured in dollars per barrel). Following Chen and Linn (2017), I compute average futures prices of natural gas and oil using all available, m, futures contracts from the trading floor of the New York

Mercantile Exchange (NYMEX). I define futures price (F_t) at time *t* as a function of the contract prices such that $F_t = \frac{1}{n}(\sum_{m=1}^{n} C_{t,m})$, where $C_{t,m}$ denotes the price of the m-th contract at time t. Contract prices and natural gas pipeline capacity data are obtained from the EIA. Pipeline capacity measures outflow volume of pipeline infrastructure expressed in million cubic feet per day (mmcf/d). Table 9 indicates that pipeline capacity increased the most in the Appalachian region with more than 30,000 mmcf added between 2007 to 2018. On the other hand, Bakken experienced the least expansion in pipeline capacity with less than 1000mmcf added over the same period. In Eagle Ford, Niobrara, Haynesville, Anadarko and Permian capacities increased by 4,141mmcf, 16,708mmcf, 16,386mmcf, 5,968mmcf and 6,920mmcf respectively.

In the time-to-event (survival) analysis of DUC duration status, I use individual well level data from January 2000 to July 2018. DUC duration status for an individual unconventional well is the number of days between the end of stage one[37] and completion or beginning of gas production. Completion date in the analysis is the earliest of the reported well completion date or the date of first reported production[38]. Summary statistics of DUC duration are presented in Table 9.

3.3 Empirical Strategy

The empirical strategy includes: a) the analysis of natural gas production in terms of drilling rig counts and producing wells using linear fixed effects and vector autoregressive models, b) the analysis of DUC counts within and across regions using linear fixed effects regressions, and c) the analysis of individual DUC duration status using survival analysis technique.

[37]Following EIA methodology, I assume that stage one takes 20 days on average.

[38]Many wells are completed/fractured more than once, and the data do not indicate whether a specific completion date corresponds to first completion or a recompletion. Therefore, I use the earlier of the first production or completion dates to avoid re-completion entries.

3.3.1. Natural gas production

I first use a linear regression model in double log form to explore the effect of (lagged) rig count (RC) and producing wells (PW) on natural gas production (NGP) individually and in combination. Next, I estimate autoregressive models as a robustness check. I test for unit roots using Phillips-Perron (Phillips and Perron, 1988), Augmented Dickey-Fuller (Dickey and Fuller, 1981) and panel Levin-Lin-Chu (Levin, et al., 2002) statistics. Subsequently, I conduct a panel cointegration analysis to determine the long-run relationship between natural gas production, rig count, and the number of producing wells[39]. The Pedroni's heterogeneous panel cointegration test is used to test for the group and bivariate cointegration relationships. I compute four panel and three group statistics following Neal (2014) based on the 'within' and the 'between' dimensions respectively (Pedroni 1999, 2004). I also test for cointegration within each region using the Johansen test (Johansen, 1988, 1995a, b). I proceed with estimating a panel VAR with generalized methods of moments (Abrigo and Love, 2016). Next, I estimate each region's VEC (vector error correction) model to account for cointegration within regions (Engle and Granger, 1987). The VEC model is specified as follows:

$$\begin{aligned} \Delta Y_{kt} &= \alpha_k + \delta\eta_{kt-1} + \textstyle\sum_{i=1}^{p} \beta_{ki}\, \Delta Y_{kt-i} + \\ &\quad + \textstyle\sum_{i=1}^{p} \Phi_{1ki}\, \Delta X_{1kt-i} + .. + \textstyle\sum_{i=1}^{p} \Phi_{jki}\, \Delta X_{jkt-i} + \varepsilon_{kt} \end{aligned} \tag{3.1}$$

where Δ is the first difference operator; $\boldsymbol{Y_{kt}}$ is natural gas production in log form in each region $\boldsymbol{k}$ at period $\boldsymbol{t}$; $\boldsymbol{X_j}$ is the j-th explanatory variable in log form; $\boldsymbol{\eta}$ are the residuals from the cointegration vector; $\boldsymbol{p}$ is the optimal lag length; $\boldsymbol{\alpha_k}$ is the intercept, and $\boldsymbol{\varepsilon_t}$ is the error term.

[39] Following Liew (2004), Hannan-Quinn criterion (HQC) (Hannan and Quinn 1979) is used to determine the appropriate lag length for each series in each region.

3.3.2. DUC Counts

To examine the growth in the number of DUCs, I use regional fixed effects regression models in log-log form with and without time fixed effects[40], with first differences, and standardized variables. The independent variables include pipeline capacity, drilling rig count, natural gas and oil futures prices. Futures prices (FP) rather than spot prices are used following Chen and Linn (2017) who showed that futures prices have a more significant effect on natural gas production than spot prices. The futures prices (FP) are lagged to account for the time that it takes the operators to initiate production in response to price movements (Osmundsen et al., 2015). I use standardized variables obtained by subtracting the mean (across regions and within regions) and pipeline capacity expressed in first difference to estimate the fixed effects regression model[41]. Standardization approach reduces the scale of variables but preserves the interpretation of the regression coefficients to represent the mean change in the DUC given a unit change in the independent variable.

3.3.3. DUC Status Duration

In this analysis, I am interested in examining the factors that influence the length of time that operators take to complete the drilled wells. Time to event (duration/survival) analysis (see Sy and Taylor, 2000; Box-Steffensmeier and Zorn, 2001; Fleming and Harrington 2011; Hernandez and Dresdner, 2010) is used to analyze DUC duration data. I define a random variable $\boldsymbol{T}$ with a continuous probability distribution function $f(t)$ to represent DUC duration, or the number of days from the end of drilling to completion. The probability that a drilled well is completed in *t* days is given by $F(t) = Prob(T < t)$. Correspondingly, the survival function, or the probability of a drilled well not being completed in *t* days, is $S(t) = 1 - F(t)$. The hazard rate ($\lambda(t) = f(t)/S(t)$), is the probability that a drilled well will be completed at time, t, given that it was not completed prior to *t*. I use semi-

[40]Hausman test (Chi2(5) =78.04; Prob>Chi2=0.00) indicted superiority of Fixed Effects regression over a Random Effects model. Joint F test results (F (135, 820) =1.92 Prob>F=0.00) suggest including time fixed effects.
[41]After standardization all VIFs were less than 5 with mean of 2.81 (Hair, Anderson, Tatham, and Black, 1995).

parametric[42] Cox proportional hazard model (equation (3.2)) (Cox, 1972) to represent the hazard function in the DUC duration analysis (Stogiannis et al. 2011).

$$\lambda(t|x, \boldsymbol{\beta}) = \lambda_0(t) exp\ (\boldsymbol{X}'\beta) \tag{3.2}$$

where β is a vector of unknown parameters of X covariates, $\lambda_0(t)$ is the baseline hazard function when $\lambda(t|x = 0) = \lambda_0(t)$ and can take any form as a function of *t*. The effects of covariates can be represented in various specifications of the hazard function.

3.4 Results

I start with examining the difference in the relationship between natural gas production and rig count (RC) before and after February 2009[43]. In addition to the expansion in unconventional gas production, this breakpoint is also close to the economic downturn and to the beginning of the new US administration. Each of these factors could have contributed to the structural break timing. Nevertheless, I believe that the breakpoint adequately reflects the changes in natural gas production series and enables meaningful comparison of production pre and post 2009.

Table 10: Split Sample Regional Fixed Effects Results for Aggregate NGP

Dependent – NGP	Before Feb 2009	After Feb 2009
Rig Count$_{t-1}$	0.212 (0.04)***	-0.048 (0.03)
Constant	13.55 (0.17)***	15.54 (0.15)***
R-sq	0.17	0.010
Observations	n=7, T=25, N=175	n=7, T=113, N=791

*Note: Significance values 1%***, 5%**, 10%*; Standard Errors in Brackets*

[42]I also estimate parametric specifications including exponential, Weibull and Gompertz functions. These results are available on request.

[43]I test for the presence of a structural break using Wald-type tests (Vogelsang, 1997; Andrews 1993; Andrews and Ploberger 1994) in the linear regression of natural gas production (NGP) and rig count (RC). I estimate a linear regression model and compute the S-wald test statistic for an unknown break. I also used this method to identify the breaks (B_i) for each region independently. The results show May 2010 for Anadarko, August 2012 for Appalachia, December 2012 for Bakken, February 2013 for Eagle Ford, February 2009 for Haynesville and January 2014 for Niobrara and Permian.

The results from regional fixed effects regression models with lagged RC are presented in Table 10. These results show a significant change in the explanatory power of lagged RC for natural gas production (NGP). The rig count is positively correlated with natural gas production prior to February 2009. However, after February 2009 RC has a statistically insignificant relationship with natural gas production and a weaker explanatory power. A similar loss of explanatory power of RC is found with heterogeneous break point dates across regions (see Table 3.A1 in the Appendix).

3.4.1. Determinants of Natural Gas Production (NGP)

Table 11 shows regression results with region fixed effects and logged NGP as the dependent variable. Three model results are presented. R-squared values show that Models 2 and 3, which include producing wells (PW) explain more of the variation in NGP than Model 1 (with only RC). The marginal contribution of producing wells as an explanatory variable relative to the rig count is significant, as revealed by the difference in R-squared values between Models 1 and 2. Comparison of Models 2 and 3 illustrates that although rig count is statistically significant and remains to be a meaningful determinant of NGP, its marginal contribution to explaining variation in natural gas production is smaller relative to the number of producing wells. These results are robust under heterogeneous break period specification across producing regions (see Appendix Table 3.A2).

Table 11: Region and Time Fixed Effects Regression Results for Aggregate NGP

NGP-Dep	Model 1	Model 2	Model 3
Rig Count$_{t-1}$	0.332 (0.03)***		0.274 (0.03)***
Producing Wells		0.524 (0.04)***	0.468 (0.03)***
Feb 2009	1.413 (0.22)***	1.044 (0.22)***	1.093 (0.21)***
Constant	12.94 (0.22)***	9.906 (0.41)***	9.132 (0.41)***
R-sq	0.58	0.61	0.64
Observations	Balanced Panel n=7, T=138, N=966		

*Note: Significance values 1%***, 5%**, 10%*; Standard errors in brackets; Data from 2007-2018*

To explore the relationship at the regional scale, I estimate Models 1, 2 and 3 for each region individually. The results presented in Table 12 are consistent with the results in Table 11, with all but two of the regions showing statistically significant effects of producing wells (PW).

Table 12: Regional Regression Results (Determinants of NGP)

Region	Model 1	Model 2	Model 3
Anadarko			
Rig Count$_{t-1}$	-0.003 (0.03)		0.002 (0.02)
Producing Wells		0.894 (0.07)***	0.908 (0.07)***
Feb 2009	0.202 (0.03)***	-0.126 (0.03)***	-0.126 (0.03)***
Adj R-sq	0.230	0.633	0.630
Appalachia			
Rig Count$_{t-1}$	-0.663 (0.19)***		-0.521 (0.16)***
Producing Wells		3.978 (0.50)***	3.874 (0.49)***
Feb 2009	2.222 (0.20)***	0.596 (0.22)***	0.915 (0.24)***
Adj R-sq	0.482	0.621	0.642
Bakken			
Rig Count$_{t-1}$	-0.264 (0.09)***		-0.083 (0.03)**
Producing Wells		0.896 (0.03)***	0.884 (0.03)***
Feb 2009	1.571 (0.15)***	-0.318 (0.08)***	-0.245 (0.09)***
Adj R-sq	0.436	0.916	0.919
Eagle Ford			
Rig Count$_{t-1}$	0.152 (0.06)**		0.153 (0.02)***
Producing Wells		1.525 (0.05)***	1.530 (0.04)***
Feb 2009	0.838 (0.12)***	-0.235 (0.05)***	-0.337 (0.04)***
Adj R-sq	0.379	0.931	0.937
Haynesville			
Rig Count$_{t-1}$	0.077 (0.02)***		0.160 (0.03)***
Producing Wells		0.177 (0.14)	0.771 (0.17)***
Feb 2009	0.653 (0.05)***	0.490 (0.08)***	0.391 (0.07)***
Adj R-sq	0.587	0.571	0.638
Niobrara			
Rig Count$_{t-1}$	0.011 (0.01)		0.010 (0.02)
Producing Wells		-0.023 (0.03)	-0.028 (0.03)
Feb 2009	0.122 (0.02)***	0.136 (0.02)	0.138 (0.02)***
Adj R-sq	0.363	0.382	0.203
Permian			
Rig Count$_{t-1}$	-0.006 (0.05)		-0.121 (0.04)***
Producing Wells		1.255 (0.12)***	1.390 (0.13)***
Feb 2009	0.172 (0.06)***	-0.387 (0.07)***	-0.408 (0.07)***
Adj R-sq	0.051	0.457	0.497

*Note: Significance values 1%***, 5%**, 10%*; Standard errors in brackets; Data from 2007-2018*

In some of the regions, rig count has a negative coefficient as natural gas production increased despite the declining number of active rigs. The estimated adjusted R-squared varies among regions and between models. However, in all cases, Models 2 and 3, which include the number of producing wells, show better fits compared to Model 1. The rig count is a significant indicator for natural gas production in some regions. However, in most regions the rig count is not as informative as the number of producing wells, which accounts for well completions. Similar conclusions are reached in the models with heterogeneous break points across regions (see Table 3.A3 in the Appendix).

In Table 13, I show the results from the regression where new wells are separated from older (legacy) wells. In this model, new wells represent cumulative number of wells that started producing up to three months ago. New well completions reflect the effect of higher initial productivity of new wells and have a statistically significant effect[44]. The new wells contribute to total gas production only after completion, which can be delayed indefinitely after drilling. The delays in completion weaken the correspondence between drilling rates and aggregate gas production. Hence, well completion decisions have a significant impact on aggregate natural gas production following the growth in UOG production. The conclusions are robust with heterogeneous breakpoints across regions (see Table 3.A4 in the Appendix).

Table 13: Regional and Time Fixed Effects Regression Results (NGP and New Wells)

Dependent – ΔNGP	Log-log form
Legacy Wells	-0.012 (0.00)***
New Wells	0.009 (0.00)***
Feb 2009	0.042 (0.02)***
Constant	0.070 (0.03)**
R-sq	0.26

*Note: Significance values 1%***, 5%**, 10%*; Standard errors in brackets*

[44] I also estimated the model where new wells include those that have started producing longer than three months ago. The results, available upon request, confirm declining productivity after approximately a year.

Next, I turn to the panel vector autoregressive models. First, I perform several diagnostic tests. Unit root tests indicate that all variables are non-stationary in levels at the regional and aggregate scales. However, I reject the null hypothesis that the differenced variables contain a unit root at 1% significance level (see Table 3.A5 in the Appendix for the first-differenced variables, with and without a trend). I use a lag length of four as determined by HQC test (see Table 3.A6 in the Appendix) in estimating the autoregressive models. The Pedroni's heterogeneous panel cointegration test is used to determine the long-run relationships between variables (see Table 3.A7 in the Appendix), and indicates that panel rho-statistic, panel PP statistic, group rho-statistics and group PP-statistics fail to reject the null hypothesis of no cointegration at the 0.1 significance level[45]. However, panel ADF t-statistic and group ADF-statistics reject the null hypothesis at the 0.05 significance level. Conversely, the Johansen test for cointegration (Johansen, 1988, 1995a, b) reveals cointegration within regions between some of the variables in the specifications (see Appendix Table 3.A8). Therefore, I reject the null of zero co-integrating vectors within regions using the trace statistic and conclude that there is at least one co-integrating vector in the specifications, which include natural gas production (NGP), rig count (RC) and producing wells (PW).

The results for the panel vector autoregressive models with regional fixed effects are presented in the Appendix (see Table 3.A9). The rig count is statistically not significant in the first three models. On the other hand, the lagged number of producing wells is significant. I also estimate the Vector Error Correction model with NGP as a function of RC and PW for each region. Results are presented in the Appendix section (see Table 3.A10). The rig count has a statistically insignificant effect in three of the seven regions. In Bakken, Eagle Ford, Niobrara and Permian regions, the rig count has a

[45]The panel VEC estimation follows two steps. First is the estimation of long run relationship using the following model, $Y_{k,t} = \alpha_k + \delta_k t + \sum_{i=1}^{n} \beta_i X_{i,k,t} + \varepsilon_{kt}$, to obtain the estimated residuals ε_{kt} which form the error correction term in the panel VEC model (see Jiang and Liu, 2014). In the second step, equation 1 is estimated as a panel VAR with the error correction term.

negative and significant coefficient indicating growth in natural gas production despite a declining number of active rigs. This is consistent with the previous results and with the report by the Federal Reserve Bank of Dallas (2019). These results suggest that well productivity and the number of producing wells, which depends on well completion rates, are important determinants of natural gas production.

Overall, the results show that there is a significant relationship between the cumulative number of producing wells and natural gas production. However, the strength of the relationship differs across regions. In comparison, the drilling rig count is statistically weaker in explaining natural gas production. Delays in unconventional well completions, and growth in the number of DUCs, have introduced an additional layer of disparity between drilling rig count and natural gas production. I examine the determinants of the number of DUCs in the next section.

3.4.2. DUCs Analysis

Region and time fixed effects models are used to examine the number of DUCs as a function of pipeline capacity (Cap), rig count (RC), and natural gas and oil futures prices (FP). The results in Table 14 are consistent with expectations. I observe that futures prices of natural gas and oil have statistically significant and negative effects on the number of DUC numbers. When futures prices are high, more wells are completed, and DUC numbers decline. This result is consistent with operators selling at favorable prices to cover well completion costs by taking advantage of high initial well production rates. With futures and forward contracts locked in, the operators attract investors to front the money needed for well completion. This result supports the insight that operators defer well completions, leading to high DUC numbers, in anticipation of better oil and natural gas prices (Andrien, 2016; Kleinberg, 2018).

Table 14: Drilled and Un-Completed Well Analysis Regional Regression Results

	Region Fixed Effects		Region and Time Fixed Effects	
DUC - dependent	A. Log-log	B. Log-log	C. Variables standardized across regions	D. Variables standardized by region
Pipeline Capacity	1.668 (0.86)		0.329 (0.17)	0.232 (0.24)
ΔPipeline Capacity	-	2.274 (1.73)	-	-
Rig Count$_{t-1}$	0.448 (0.10)***	0.585 (0.14)***	0.485 (0.11)***	0.412 (0.09)***
NG Future Price	-0.213 (0.14)	-2.337 (0.69)**	-0.636 (0.16)***	-1.493 (0.73)*
Oil Future Price	-0.031 (0.15)	-4.112 (1.01)***	-0.765 (0.16)***	-1.841 (0.86)*
Time	0.007 (0.00)**			
Constant	-11.75 (8.71)	24.34 (4.48)***	-0.218 (0.13)	-1.008 (0.39)**
Adj R-sq	0.717	0.735	0.792	0.721
Observations	966	966	966	966

*Note: Significance values 1%***, 5%**, 10%*; Robust standard errors in brackets; Data from 2007-2018*

Region fixed effects regression results show that pipeline infrastructure is not a statistically significant factor in explaining DUC numbers[46]. Statistical insignificance of pipeline capacity in these models can be due to a lack of variability in pipeline capacity within each region over time. The individual region results in Table 15 confirm the results from the aggregate analysis.

Table 15: OLS Log-log Regression Results for DUC Well Analysis per Region

Dep- DUC counts	Anadarko	Appalachia	Bakken	Eagle Ford	Haynesville	Niobrara	Permian
ΔPipeline Capacity	-0.832	0.767	-0.861	-0.544	0.374	-0.081	-0.781
	(0.35)	(2.00)	(1.45)	(1.47)	(1.17)	(0.26)	(1.95)
Rig Count$_{t-1}$	0.281***	0.462*	0.278 ***	0.510 ***	0.247***	0.180***	0.354 ***
	(0.07)	(0.24)	(0.07)	(0.05)	(0.02)	(0.05)	(0.03)
NG Future Price	-1.089***	-2.949***	-1.363***	-0.934***	-0.666 ***	-0.262***	-0.391***
	(0.08)	(0.31)	(0.12)	(0.10)	(0.06)	(0.07)	(0.06)
Oil Future Price	0.079	0.646	0.158	-0.121	-0.295***	-0.234 ***	-0.382***
	(0.10)	(0.41)	(0.17)	(0.12)	(0.05)	(0.08)	(0.08)
Constant	6.735***	5.747***	6.624***	6.442***	5.035***	8.302***	7.937 ***
	(0.35)	(0.89)	(0.46)	(0.35)	(0.18)	(0.27)	(0.23)
R-sq	0.740	0.747	0.728	0.831	0.634	0.532	0.720
Observations	138	138	138	138	138	138	138

*Note: Significance values 1%***, 5%**, 10%*; Standard errors in brackets; Data from 2007-2018*

[46]I also estimated a regional and time fixed effects regression model using first differences of the explanatory variables. The results show significant negative effect of oil and gas futures prices on DUC growth. However, pipeline capacity and drilling activity are not significant. These results are available on request.

Table 15 show that rig count and futures prices have positive and negative effects on DUC numbers, respectively. The results also show that, as one would expect, an increase in drilling activity, measured in terms of the number of active drilling rigs, has a statistically significant and positive effect on the number of DUCs. All else constant, greater drilling activities lead to a greater number of DUCs.

3.4.3. DUC Status Duration Analysis

Next, I examine the length of time that operators take to complete each unconventional well. I use the well level DUC duration status data to examine completion timing. Non-parametric survival functions are presented in Figure 9 using data from 2000 to 2018. The Kaplan-Meier survival curves show the proportion of wells that remain uncompleted over time. Most wells (about 90%) are completed within a year. An insignificant number of outlier DUCs (about 0.3%) remain uncompleted after five years. In this study, such wells are treated as "dead"[47] DUCs and are excluded from the regression analyses.

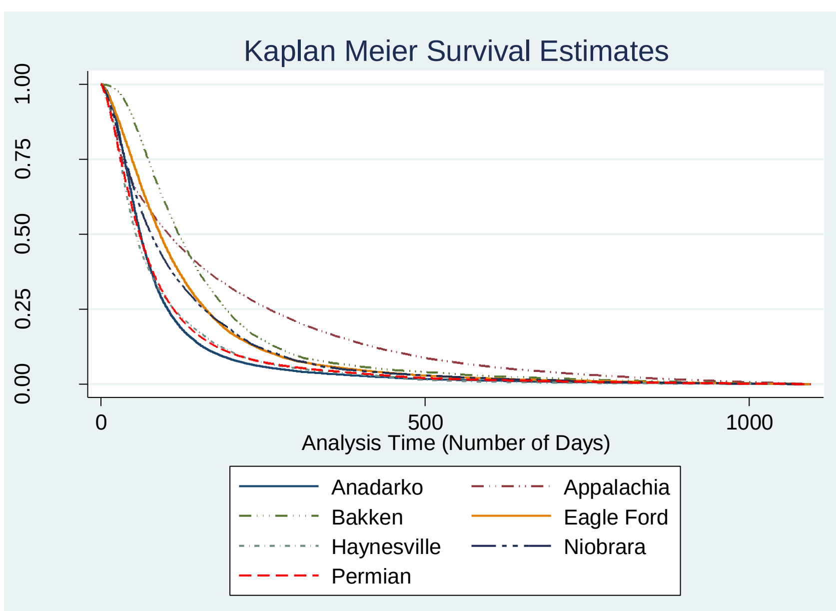

Figure 9: Kaplan-Meier survival curves

[47] Example of such definition can be found in Andrien (2016) where "dead" DUCs are defined as wells which fail to be completed even at better oil and gas prices.

I use linear regression and time-to-event (survival) models to obtain statistical estimates for the factors that explain the length of time taken to complete drilled wells. The generalized linear model is used to illustrate the general baseline relationship between DUC duration and the explanatory variables. However, survival analysis is more appropriate to represent the duration data adequately and to provide a more detailed account using both the survival and hazard functions. The survival function represents the probability that a well remains uncompleted at any given time, while the hazard function gives the probability that a well will be completed in a given period assuming that it has not yet been completed.

The Results for the generalized linear (column A) and semi-parametric Cox proportional (columns B and C) models with logged days of DUC duration status are presented in Table 16. Cross region variation is captured using dummy variables with Anadarko as the base category. Generalized linear model results show that all variables are statistically significant with expected signs. Pipeline capacity, natural gas and oil futures prices have statistically significant and negative effects on the duration of the DUC status[48]. On the other hand, well depth has a positive effect on DUC duration. Interpretation of the coefficients in the Cox proportional survival model (column B) should be opposite of the estimated signs (see Teachman and Hayward, 1993 for interpretation of hazard models). A positive coefficient indicates a negative effect on the probability that a well remains uncompleted (longer DUC duration). For example, the results show that an increase in natural gas and oil prices decreases the probability that a well will remain uncompleted at any given time, which implies a decrease in DUC duration status. On the other hand, the length of the unconventional well has a positive effect on the duration of DUC status. Similarly, I observe that from 2000 to 2018, the probability that an unconventional well remains uncompleted at any given time has increased.

[48]Pipeline capacity limitations have been especially prominent in the Permian basin leading to negative natural gas prices and increase in the number of DUCs (Addison, 2018; Surran, 2019).

The coefficient estimates for the hazard rates (the probability that a well will be completed at time *t* given that the well has not been completed prior to *t)* in column C are consistent with the estimates from the linear regression model results (column A) and prior expectations.

Table 16: DUC Duration Analysis Results

Variables	Generalized linear model	Semi-Parametric Cox Proportional Model	
Dep-DUC Duration	A. Coef.	B. Coef.	C. Hazard Ratio
LL	-139760	-1346626	-1401168
LR Chi2(12)		20062 (0.00)	20062 (0.00)
NG Future Price	-0.041 (0.01)***	0.052 (0.01)***	1.053 (0.01)**
Oil Future Price	-0.051 (0.01)***	0.118 (0.01)***	1.126 (0.01)***
Pipeline Capacity	-0.502 (0.03)***	1.013 (0.05)***	2.753 (0.13)***
Gas Well[49]	0.232 (0.01)***	-0.269 (0.01)***	0.764 (0.01)***
Well Measured Depth	0.498 (0.01)***	-0.350 (0.01)***	0.705 (0.00)***
Time	0.0001(0.00)***	-0.0002(0.00)***	0.999 (0.00)***
Appalachia	1.477 (0.03)***	-1.960 (0.04)***	0.141 (0.01)***
Bakken	-0.320 (0.03)***	0.651 (0.04)***	1.917 (0.08)***
Eagle Ford	-0.225 (0.03)***	0.594 (0.05)***	1.811 (0.09)***
Haynesville	0.544 (0.03)***	-1.061 (0.04)***	0.346 (0.02)***
Niobrara	0.621 (0.01)***	-0.869 (0.02)***	0.419 (0.01)***
Permian	0.288 (0.01)***	-0.411 (0.01)***	0.663 (0.01)***
Observations	126,048	127,627	127,627
Number of Completions	126,048	126,048	126,048

*Note: Significance values 1%***, 5%**, 10%*; Standard errors in brackets; Data from 2000-2018*

A hazard ratio coefficient greater (less) than one indicates that a unit increase in the covariate is associated with an increase (decrease) in the probability that a well will be completed at any given time *t,* given that it is still in DUC status at time *t-1*. For example, using the estimates from column C, all else constant, a one dollar increase in natural gas price is associated with 5.3% increase in the hazard rate. Similarly, a unit (10^3 mmcfd) increase in pipeline capacity is associated with 175% increase in hazard rate, on average across regions. This result illustrates the significance of pipeline infrastructure

[49]Gas well is a dummy variable (with 1=Natural Gas producing well and 0=Oil producing well) that captures production type as defined by operator. Wells are classified based on their gas/oil ratio (GOR).

for unconventional well completion decisions. On the other hand, a unit (10^3 ft) increase in the well depth of an unconventional well is associated with 0.295% (1-0.705) decrease in hazard rate.

The results also show that both survival and hazard rates differ significantly across regions and that gas wells are more likely to have lengthier DUC periods than primarily oil producing wells. This result, in combination with the significance of pipeline capacity, is possibly indicative of more pressing pipeline bottlenecks in natural gas supply than in oil. I also observe that well depth has a negative effect on the probability of completion at any given time. These results, in general, suggest that prices, infrastructure, and geologic variables play important roles in operators' decisions to complete unconventional gas wells. This is consistent with the results in recent literature where prices and geologic factors are reported to be significant determinants of unconventional oil and gas production decisions (Mason and Roberts, 2018; Kleinberg et al., 2018; Ikonnikova and Gülen, 2015).

3.5 Conclusion

The US natural gas production industry has experienced tremendous growth in the recent decade due to the developments in unconventional oil and gas extraction technologies. This growth has affected domestic and international energy markets (Oglend, et al., 2016), electricity generation sector (Peters and Hertel, 2017; Logan et al., 2013), industrial manufacturing sectors (Arora and Lieskovsky, 2014) and labor markets (Agerton, et al., 2017). Therefore, it is important to identify key interdependencies in the natural gas industry for appropriate market analysis and effective policy formulation. The objective of this study is to explain the observed variability in the US natural gas output in terms of the drilling rig count, the number of producing wells, and the completion of drilled unconventional wells. I am particularly interested in the observed growth of the number and duration of DUCs in recent years, given a significant increase in unconventional production.

I find that since the expansion in shale gas production, the explanatory power of rig count has declined, while the effect of the number of producing wells remained statistically significant. Therefore, new wells and completion of drilled wells are important determinants of natural gas output. The decline in the significance of rig counts as a determinant is expected given the nature of UOG production technology, where extraction requires hydraulic fracturing as an additional step, which can be delayed indefinitely. Hence, unless delays in well completion are constant across wells, the explanatory power of rig counts is expected to decline. Indeed, I observe heterogeneity in the delay of well completions and an overall increase in the number of DUCs. As a result, the statistical significance of rig counts has diminished as completion decisions have become important determinants of natural gas output.

The results show that rig count and futures prices have statistically significant effects on the number of DUCs. Aggregate, as well as region-specific results indicate that an increase in the natural gas futures prices decreases the number of DUCs. This suggests that all else constant, increase in natural gas prices motivates operators to complete existing drilled wells sooner. An increase in the price of natural gas futures decreases the probability that a well remains uncompleted and increases the probability that a well will be completed assuming it has not yet been completed. This result is consistent with producers hedging gas production to take advantage of high initial well productivity. Forward contracts and futures markets with favorable prices enable producers to pay off well completion costs faster and attract needed investment to finance well completion.

The duration model also shows that pipeline capacity has a negative effect on the duration of DUC status. This result confirms the effect of pipeline infrastructure bottlenecks in natural gas markets. While the effect of pipeline bottlenecks on natural gas prices has been recognized (Oliver et al., 2014), I show that pipeline capacity has a direct positive effect on the completion of drilled unconventional wells using data from multiple shale regions. the results are consistent with the observed negative effects of pipeline constrains on completion rates and associated negative impacts on the demand for sand, water, and fracking fleet capacity as reported in industry outlets (Davis, 2018; Andrien, 2016).

It is important to note that this study does not explicitly address the simultaneity of output, inventories, and prices. This study is the first to draw attention to the role of well completion in unconventional gas production as a factor in aggregate output. the objectives for the models of aggregate natural gas production is to point to the diminished power of rig counts and the increased role of completion decisions. I refrain from also addressing the identification issues and from claiming causal inference involving aggregate natural gas supply and prices. Future studies should examine supply of natural gas considering endogeneity of prices and inventory to support a proper causal inference for supply. In the analysis of DUC duration, I include prices as one of the factors affecting the timing of well completion decisions. In the well level analysis, causal inferences pertaining to prices and well level completion decisions are not as susceptible to the inconsistency of estimates that may be caused by price endogeneity. For individual well completion modeling, price can be reasonably treated as an exogenous factor.

The results of this study are important for natural gas operators, energy market analysts, government agencies and other stakeholders in the natural gas industry. Investors, operators, market analysts and policy makers rely on natural gas production information to support investment strategies, facilitate production decisions, improve market analysis, and formulate regulatory policies. Thus, it is important to have access to the best available information about the primary determinants of natural gas production. EIA produces a monthly report (Drilling Productivity Report) which uses data on drilling rig counts, drilling productivity and production in natural gas wells to develop regional forecasts of natural gas production. In this study, I show that the information about drilled but uncompleted wells can be meaningful for improving such projections.

I also show that infrastructure constraints, like pipeline bottlenecks, can have important implications for well completion decisions and natural gas output in the US. The implications of such bottlenecks are important for coordinating increasingly interdependent electricity and natural gas markets (Mugabe et al., 2020) considering reliability (Moeller, 2012; US Department of Energy, 2015). Increased availability of shale gas has transformed the US power sector (Mugabe et al., 2020; Kerr, 2010; Rogers, 2011), and future developments in natural gas distribution infrastructure will likely have further implications for US power generation sector (Logan et al., 2013). Future analysis should examine how the US electricity sector will evolve under various natural gas distribution infrastructure bottleneck scenarios.

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APPENDIX

Table 3.A1: Split Sample Regional Fixed Effects Results for Aggregate NGP

Dependent – NGP	Before Break(i)	After Break(i)
Rig Count$_{t-1}$	0.461 (0.02)***	-0.080 (0.02)***
Constant	12.47 (0.12)***	15.97 (0.07)***
R-sq	0.45	0.05
Observations	n=7, N=444	n=7, N=522

*Note: Significance values 1%***, 5%**, 10%*; Standard errors in brackets*

Table 3.A2: Region and Time Fixed Effects Results for Aggregate NGP

NGP-Dep	Model 1	Model 2	Model 3
Rig Count$_{t-1}$	0.298 (0.03)***		0.247 (0.03)***
Producing Wells		0.512 (0.04)***	0.467 (0.04)***
Break(i)	0.427 (0.05)***	0.423 (0.05)***	0.378 (0.05)***
Constant	13.10 (0.22)***	10.01 (0.40)***	9.266 (0.40)***
R-sq	0.61	0.64	0.66
Observations	Balanced Panel n=7, T=138, N=966		

*Note: Significance values 1%***, 5%**, 10%*; Standard errors in brackets; Data from 2007-2018*

Table 3.A3: Regional Regression Results (Determinants of NGP)

Region	Model 1	Model 2	Model 3
Anadarko			
Rig Count$_{t-1}$	-0.084 (0.02)***		-0.020 (0.02)
Producing Wells		0.510 (0.08)***	0.484 (0.09)***
B_1 May 2010	0.259 (0.03)***	0.084 (0.03)***	0.097 (0.03)***
Adj R-sq	0.543	0.618	0.614
Appalachia			
Rig Count$_{t-1}$	0.421 (0.10)***		0.180 (0.09)*
Producing Wells		2.114 (0.30)***	1.902 (0.30)***
B_2 August 2012	1.972 (0.08)***	1.501 (0.09)***	1.551 (0.09)***
Adj R-sq	0.831	0.871	0.871
Bakken			
Rig Count$_{t-1}$	0.121 (0.05)**		-0.060 (0.02)***
Producing Wells		0.676 (0.02)***	0.711 (0.02)***
B_3 December 2012	1.597 (0.15)***	0.377 (0.05)***	0.311 (0.05)***
Adj R-sq	0.814	0.974	0.976
Eagle Ford			
Rig Count$_{t-1}$	0.238 (0.03)**		0.147 (0.02)***
Producing Wells		1.072 (0.06)***	0.921 (0.06)***
B_4 February 2013	1.044 (0.04)***	0.292 (0.06)***	0.381 (0.04)***
Adj R-sq	0.873	0.933	0.958
Haynesville			
Rig Count$_{t-1}$	0.077 (0.02)***		0.160 (0.03)***
Producing Wells		0.177 (0.14)	0.771 (0.17)***
B_5 February 2009	0.653 (0.05)***	0.490 (0.08)***	0.391 (0.07)***
Adj R-sq	0.587	0.571	0.638
Niobrara			
Rig Count$_{t-1}$	-0.046 (0.01)***		-0.034 (0.01)***
Producing Wells		0.184 (0.02)***	0.161 (0.02)***
B_6 January 2014	-0.015 (0.01)	-0.066 (0.02)***	-0.077 (0.02)***
Adj R-sq	0.061	0.284	0.283
Permian			
Rig Count$_{t-1}$	-0.019 (0.03)		-0.011 (0.03)
Producing Wells		-0.073 (0.07)	-0.065 (0.08)
B_7 January 2014	0.462 (0.02)***	0.484 (0.04)***	0.481 (0.03)***
Adj R-sq	0.750	0.752	0.749

*Note: Significance values 1%***, 5%**, 10%*; Standard Errors in Brackets; Data from 2007-2018*

Table 3.A4: Region and Time Fixed Effects Results (NGP and New Wells)

Dependent – ΔNGP	Log-log form
Legacy Wells	-0.012 (0.00)***
New Wells	0.009 (0.00)***
Break(i)	0.002 (0.02)
Constant	0.072 (0.03)**
R-sq	0.26

*Note: Significance values 1%***, 5%**, 10%*; Standard errors in brackets*

Table 3.A5: Unit Root Tests

	With trend	Without trend	With trend	Without trend
Variables	Phillips-Perron		Augmented Dickey-Fuller	
	Regional Aggregate			
ΔNG Production	-50.060***	-48.412***	-35.003***	-34.928***
ΔRig Count	-5.636***	-5.629***	-5.087***	-5.085***
ΔNG Futures price	-12.862***	-12.866***	-12.903***	-12.903***
ΔOil Futures prices	-5.621***	-5.617***	-7.071***	-7.094***
	Levin-Lin-Chu		Augmented Dickey-Fuller	
	Anadarko			
ΔRig Count	-4.987***	-4.985***	-4.912***	-4.929***
ΔNG Production	-12.601***	-12.451***	-12.412***	-12.311***
ΔProducing Wells	96.47	63.152	-18.883***	-18.164***
	Appalachia			
ΔRig Count	-5.702***	-5.585***	-5.617***	-5.522***
ΔNG Production	-8.416***	-7.270***	-8.290***	-7.188***
ΔProducing Wells	-14.339***	-12.918***	-19.903***	-19.919***
	Bakken			
ΔRig Count	-4.820***	-4.679***	-4.747***	-4.626***
ΔNG Production	-10.783***	-10.031***	-10.620***	-9.918***
ΔProducing Wells	157.528	126.49	2.733	2.262
	Eagle Ford			
ΔRig Count	-4.860***	-4.758***	-4.786***	-4.705***
ΔNG Production	-5.759***	-5.758***	-5.672***	-5.693***
ΔProducing Wells	3.407	1.672	-9.951***	-9.76***
	Haynesville			
ΔRig Count	-4.813***	-4.800***	-4.741***	-4.746***
ΔNG Production	-4.571***	-4.565***	-4.502***	-4.514***
ΔProducing Wells	-17.226***	-6.157***	-9.597***	-8.984***
	Niobrara			
ΔRig Count	-5.781***	-5.776***	-5.694***	-5.711***
ΔNG Production	-8.550***	-8.428***	-8.421***	-8.333***
ΔProducing Wells	30.459	23.813	-21.602***	-20.942***
	Permian			
ΔRig Count	-4.185***	-4.182***	-4.122**	-4.135***
ΔNG Production	-9.870***	-8.215***	-9.721***	-8.122***
ΔProducing Wells	-9.036***	-7.827***	-17.335***	-16.921***

*Note: Significance levels ***1%; **5%; *10%*

Table 3.A6: Variable Lag Length

Series→	NGP & RC		NGP & PW		NGP, RC & PW	
Region	#of lags (AIC)	#of lags (HQIC)	#of lags (AIC)	#of lags (HQIC)	#of lags (AIC)	#of lags (HQIC)
Anadarko	4 (-7.13)	3 (-6.99)	4 (-7.79)	4 (-7.61)	4 (-10.70)	3(-10.36)
Appalachia	3 (-7.14)	2 (-7.02)	4 (-5.87)	1 (-5.75)	2 (-8.94)	2(-8.75)
Bakken	3 (-6.57)	2 (-6.45)	1 (-4.00)	1 (-3.93)	3(-6.76)	2(-6.57)
Eagle Ford	2 (-7.14)	2 (-7.03)	4 (-9.20)	4 (-9.03)	4 (-11.54)	4 (-11.20)
Haynesville	2 (-7.22)	2 (-7.12)	4 (-10.03)	4 (-9.85)	3 (-12.29)	3 (-12.03)
Niobrara	2 (-7.69)	2 (-7.58)	2 (-7.90)	2 (-7.79)	2 (-10.26)	2 (-10.07)
Permian	2 (-7.30)	2 (-7.19)	2 (-7.80)	2 (-7.69)	2 (-10.85)	2 (-10.66)

AIC/HQIC level in parenthesis

Table 3.A7: Pedroni Panel Test for Cointegration

Test Statistic	Panel Statistics	Group Statistics
V	-1.782 (1.93)	.
Rho	-7.322 (2.00)	-17.73 (2.00)
PP	-3.066 (2.00)	-5.013 (2.00)
Adf	2.084 (0.04)**	2.084 (0.01)***

*Note: P-values in parenthesis; Significance levels ***1%; **5%; *10%*

Table 3.A8: Johansen Test for Cointegration

	Model 1	Model 2	Model 3
	NGP & RC	NGP & PW	NGP, RC & PW
Region	Rank	Rank	Rank
Anadarko	0 (6.97)*	0 (13.44)*	2 (0.59)*
Appalachia	1 (2.76)*	1 (2.15)*	2 (3.22)*
Bakken	1 (1.66)*	0 (10.12)*	1 (11.99)*
Eagle Ford	1 (2.31)*	0 (10.33)*	1 (6.23)*
Haynesville	1 (3.57)*	0 (13.98)*	1 (12.82)*
Niobrara	0 (14.47)*	1 (1.17)*	0 (22.86)*
Permian	1 (3.25)*	1 (0.01)*	1 (6.24)*

Trace statistic level in parenthesis

Table 3.A9: Region Panel Vector Autoregressive (PVAR) Model Results

	Model 1	Model 2	Model 3	Model 4
ΔNatural Gas Production				
LD	-0.012 (0.04)	-0.013 (0.04)	-0.021 (0.04)	-0.038 (0.04)
L2D		0.067 (0.04)	0.072 (0.04)*	0.063 (0.04)
L3D			0.150 (0.04)***	0.157 (0.04)***
L4D				0.114 (0.04)***
ΔRig Count				
LD	0.002 (0.01)	-0.010 (0.02)	-0.009 (0.02)	-0.009 (0.02)
L2D		0.021 (0.02)	0.015 (0.02)	0.014 (0.02)
L3D			0.010 (0.01)	-0.011 (0.01)
				0.025 (0.01)**
ΔProducing Wells				
LD	0.036 (0.02)**	0.040 (0.02)**	0.034 (0.02)	0.027 (0.02)
L2D		0.006 (0.02)	0.010 (0.02)	-0.003 (0.03)
L3D			0.005 (0.02)	-0.001 (0.02)
				-0.003 (0.01)

*Note: Significance values 1%***, 5%**, 10%*; Standard errors in brackets*

Table 3.A10: Regional Vector Error Correction (VEC) Model Results

Variables	Anadarko	Appalachia	Bakken	Eagle Ford	Haynesville	Niobrara	Permian
Error	-1.730***	0.005	-0.779***	-0.365***	-0.140**	-0.648***	-0.799***
Correction	(0.24)	(0.01)	(0.18)	(0.09)	(0.06)	(0.15)	(0.17)
ΔNatural Gas Production							
LD	0.411***	-0.979***	-0.137	-0.471***	-0.588***	-0.490***	-0.364**
	(0.20)	(0.09)	(0.16)	(0.10)	(0.09)	(0.14)	(0.16)
L2D	0.051	-0.570***	-0.146	-0.380***	-0.455***	-0.354***	-0.227
	(0.14)	(0.12)	(0.13)	(0.10)	(0.10)	(0.12)	(0.14)
L3D	-0.013	-0.176	-0.010	-0.194**	-0.158	-0.143	-0.043
	(0.09)	(0.09)	(0.09)	(0.08)	(0.09)	(0.08)	(0.09)
ΔRig Count							
LD	0.064	0.005	-0.098	-0.100***	-0.027	-0.053**	-0.114**
	(0.04)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.05)
L2D	-0.022	0.079	-0.156***	-0.037	-0.005	-0.016	-0.008
	(0.04)	(0.06)	(0.05)	(0.03)	(0.03)	(0.03)	(0.05)
L3D	-0.078	0.048	-0.057	-0.010	-0.023	-0.022	-0.013
	(0.04)	(0.05)	(0.05)	(0.02)	(0.03)	(0.02)	(0.05)
ΔProducing Wells							
LD	0.606***	-0.056	-0.026	-0.647***	0.076	-0.330***	0.840***
	(0.11)	(0.09)	(0.66)	(0.20)	(0.18)	(0.08)	(0.16)
L2D	0.407	-0.035	0.244	0.372	-0.510	-0.246**	0.565***
	(0.86)	(0.06)	(0.70)	(0.38)	(0.38)	(0.12)	(0.12)
L3D	1.622	-0.011	0.037	-0.129	-0.949	-0.127	0.223***
	(0.86)	(0.03)	(0.65)	(0.63)	(1.04)	(0.10)	(0.07)
R-sq	0.70	0.57	0.49	0.46	0.38	0.59	0.65

*Note: Significance values 1%***, 5%**, 10%*; Standard errors in brackets*